WATER DISTRIBUTION NETWORK MODELING: HYDROINFORMATICS APPROACH

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SUMMARY

Water distribution network, a complex system consisting of elements including reservoirs, pipes, valves etc., is designed to deliver water to the consumers with adequate pressure head at specific nodes. It is immensely essential to design a cost-effective and yet reliable water supply network meeting the consumers' demand. This study aims to apply evolutionary algorithm tool in water distribution network modeling. The study includes the design of new water distribution network, rehabilitation of existing water distribution network, and calibration of the network model require prior its usage in the design and rehabilitation.

The design or rehabilitation of water distribution system is a difficult task due to the presence of non-linear relationship between the head and flow; this is further compounded by the discrete nature of the decision variables (pipe diameters). The traditional approaches such as linear programming, non-linear programming and dynamic programming are computationally too cumbersome in arriving at, if at all, the global solution.

The rapid advancement of digital computer makes many applications of heuristic evolutionary algorithms in the water distribution network modeling possible and very popular to both the water engineers and researchers. Many evolutionary algorithms are available; they are, for examples, Genetic Algorithm (GA), Simulated Annealing (SA), Shuffled Frog Leaping Algorithm (SFLA), Ant Colony Optimization Algorithms (ACOAs), and GLOBE. However, most of the applied algorithms need high number of evaluations of the objective function and thus longer CPU time.

This thesis uses a model which couples an optimization technique, Shuffled Complex Evolution (SCE), and a simulation model, EPANET. The coupled model: (1) searches in all directions simultaneously within the solution space, based on Nelder and Mead simplex search technique; and (2) keeps a better delicate balance between exploration and exploitation than GA, for example. EPANET simulation model is chosen in this study because it can handle both static and dynamic loading conditions. In addition, it can also perform water quality simulation.

The model is applied to designs of new as well as existing water distribution networks and model calibration. Several case studies cited in international journals are used in this study. Two case studies considered deal with the least-cost determination of new network system. The findings show that SCE algorithm is computationally faster than the other widely used algorithms such as GA, SA, GLOBE and SFLA. The model is also tested on a real large scale water distribution network; though Kohonen Neural Network is introduced to select some initial points, SCE still yields better performance in terms of optimal network design cost. Another case study, rehabilitation of an existing network at New York, is considered. In this case study an increased demand at some parts of the network is the issue. The rehabilitation is done by introducing some new pipes in parallel of the existing pipes. Results show that SCE again converges to the optimal rehabilitation options quicker than GA, ACOAs, and SFLA.

Like any model the accuracy of input data is very essential. If incorrect values of some network parameters, such as pipe roughness coefficients (due to the wear and tear of the existing pipes) and nodal demands, are used the model will not produce good and reliable results. In such networks, parameters are calibrated. The robustness of the model in obtaining such optimal network parameters are also demonstrated on two case studies. The result shows that SCE could yield the unknown pipe roughness factors as such the simulated pressure mimics the measured pressure very well.

NOMENCLATURE

K_B = Boltzmann constant

E_i = energy at state i

T = temperature

$\|\,.\,\|$ = Euclidean norm

Q_{in} = flow into the node

Q_{out} = flow leaving the node

Q_{ext} = nodal demand

$h_{i,j}$ = head loss in the pipe connecting nodes i and j

I_P = set of pipes in the loop

J_P = set of pumps in the loop

P = loop in the network

P_E = energy added by the pump

ω = numerical conversion constant

L_k = length of the k^{th} pipe

D_k = diameter of the k^{th} pipe

β_x, γ = regression coefficients

S = population size in shuffled complex evolution

p = number of complexes in shuffled complex evolution

p_{min} = minimum number of complexes in shuffled complex evolution

Ω = feasible space

m = number of points in a complex

q = number of points in a sub-complex

α = number of consecutive offspring generated by a sub-complex

β = number of evolution steps taken by each complex

N = dimension of the search space

f_i = criterion value

D = array of S points in order of increasing function value

x_i = i^{th} point in the complex

A^k = k^{th} complex

B = array of q points in the sub-complex

u_i = i^{th} point in the sub-complex

v_i = function value associated with point u_i

ρ = probability

g = centroid

r = reflection point

f_r = criterion value of the reflected point

u_q = worst point

c = contraction point

f_c = criterion value of the contracted point

C_N = network cost

$c_k(D_k)$ = cost per unit length of the k^{th} pipe

ΔH_j = pressure violation at node j

$H_{min,j}$ = minimum pressure head requirement at node j

H_j = simulated nodal head at node j

C_P = penalty cost

p_c = penalty coefficients

NP = total number of pipes

NJ = total number of violated junctions

$RMSE$ = root mean square error

$C(k)$ = pipe roughness coefficients of the k^{th} pipe

C_{min} = lower bound of roughness coefficients

C_{max} = upper bound of roughness coefficients

AP_{it} = actual nodal pressure at node i at time t

SP_{it} = simulated nodal pressure at node i at time t

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CHAPTER 1

INTRODUCTION

1.1 GENERAL

Water, a valuable resource, is used as the main raw material by our civilization. It is usually found in lakes, rivers, reservoirs and underground sources. From the sources it is abstracted and pumped or gravitated into supply network systems. Water supply systems are mandatory for supplying water to the users. The main components of water supply systems are: (1) treatment works; (2) supply network of trunk mains and main reservoirs; (3) distribution network. The untreated raw water is conveyed to the treatment plant. The treated water is then transmitted to water users through the water distribution systems.

The water distribution system is a hydraulic infrastructure consisting of various elements such as pipes, tanks, reservoirs, pumps, and valves. All of them are crucial in delivering water of acceptable quality with specified pressure. The distribution systems can be either looped or branched. Looped systems are generally more desirable than branched system because, coupled with sufficient valving, they can provide an additional level of reliability. Moreover, in the looped system, breaking of pipe can be isolated and repaired with little impact on consumers outside the immediate area. On the other hand, in the branched system, all the consumers downstream from the break will have their water supply interrupted until the repairs are finished. Looped configuration, however, facilitates more than one path for water to reach the user, and the system capacity is greater.

Water is supplied to the consumer through looped water distribution network for domestic, commercial, industrial and irrigation uses. Hence, huge amount of money is allocated to the design of a network. So, it is essential to investigate and establish a reliable network which satisfies the following conditions (McGhee, 1991): (1) maintain water quality standard in the distribution pipes; (2) establish economic design and layout; (3) deliver adequate quantity of water; (4) maintain required hydraulic pressure; (5) assure reliability of supply during any period; (6) ensure water for every consumer during repair of any section of the system; (7) provide good quality pipes with minimum leakage. Satisfying these conditions and the elements (pipes, elevated tanks, reservoirs, pumps, and valves) of a typical water distribution network complicate the design and analysis. In addition, the flows through water distribution systems are governed by complex, nonlinear, nonconvex, and discontinuous hydraulic equations (Kessler and Shamir, 1989; Eiger et al., 1994; Dandy et at., 1996). The solution of a pipe network problem is complex. The need to overcome the complexities and to realistically model fittings, valves, pumps, storage tanks, spatial and temporal variations of water demand, and variations in water quality urges to develop water distribution network simulation model.

A water distribution network simulation model represents a real system using mathematical formulations to predict the system responses under a wide range of conditions without interrupting the actual systems (Walski et al., 2001). There are two types of simulation which are: (1) steady-state; and (2) extended period simulation. Steady-state refers to the conditions that remain constant with time. And it is necessary when simulation is performed to predict the response to a unique set of hydraulic conditions (for example, peak hour demand). Steady-state simulation determines the flows, pressure, valve position, pump operating attributes etc at a certain time. Whereas, extended period simulation determines the state of the system over time. It simulates the variation of tank water levels, pressure, flows in response to varying demand conditions (Cesario, 1995).

The simulation of hydraulic behavior of pipe network in which pressurized water is fed is not an easy task. It involves solving a set of simultaneous non-linear equations, for example; continuity equation (conservation of flow to be satisfied at each node), energy equation and the equation that relates pipe flow and head-losses, such as the Hazen-Williams, Darcy-Weisbach and Mannings equations. With the advent of soft computing technology, researchers have been interested to use this technology in problems with iterative computations. There are many useful and efficient computer programs available for water distribution network simulation. EPANET (Rossman, 1993) is one such popular simulation tool which plays an important role in the layout, design and operation of the network. The water engineers use this simulation model to determine the optimal (least-cost) pipe sizes for supplying water to the consumers or to determine the optimal network parameters (pipe roughness coefficients and nodal demands) to increase the reliability of the model. Traditional approach uses a trial and error method. They assume one trial pipe sizes or network parameters and check the adequacy of the model. If the assumed variables are not adequate to satisfy the hydraulic conditions, for example, the engineer makes further changes to the values of the variables to arrive at a workable alternative.

The optimal design of water network involves the estimation of cost for each of feasible network and the final decision is made based on this information. In contrast, the determination of network parameters is performed using some evaluation criteria to match the simulation output with actual field values. However, the use of trial and error approach in both of these cases are cumbersome and time consuming because the determination of economic decision alternatives necessitates repetitive adjustments of the variables (e.g., pipe diameters) based on hydraulic results obtained from simulation model (network solver), until some pre-defined specifications (minimum nodal pressure requirement) are met. Moreover, the complexity of the trial and error procedure increases exponentially with the number of decision variables, proposed modification and corresponding operating conditions (Wu et al., 2001). One remedial option to deal with these difficulties is to use an optimization technique that exhaustively searches for an optimum solution in the domain of available feasible space.

An optimization technique uses mathematical formulation that describes the system responses for different design parameters. The objective function and constraints are introduced to control the whole strategy. The constraints limit the decision variables within a pre-specified boundary. This technique automatically generates the variables using several deterministic and probabilistic approaches and the performance is determined by the objective function. In the field of water distribution network modeling (optimal design of water distribution network and calibration of the model), optimization technique has become a popular tool. However, design optimization and calibration of the water distribution network model are also nonlinear and multimodal in nature. Kessler and Shamir (1989) described that the optimal network design is quite complicated due to nonlinear relationship between flow and head loss and the presence of discrete variables, such as market sizes of pipes. In addition, the objective function, which represents the cost of the network, is nonlinear, non-smooth and non-convex. Gessler (1985) also described the following which increases the difficulties associated with pipe network design:

1. The pipe sizes are not continuous variable because they are to be selected from a list of the available sizes. Many optimization techniques consider the continuous variables; however, after the end of the program, the rounding off of the continuous diameters may lead to a non-optimal solution or even an infeasible solution;
2. The objective function which represents the cost of the network is arbitrary. The mathematical approximation may lead to wrong results;
3. The objective function of a looped network may have several local minima; and
4. Pressure requirements may vary with changing demand scenario (peak demand, average demand, and fire demand). Several demand scenarios should be considered in the optimization.

Many of the common deterministic optimization methods (Linear Programming, Non-linear Programming and Dynamic Programming) cannot locate the global optimum solution of these problems and take tremendously long computational time to get even a feasible solution.

Recently, researchers have developed various probabilistic approaches to solve the global solution of optimization problems. Some optimization tools from the evolutionary algorithms are Genetic Algorithm (GA) (Goldberg, 1989), Structured Messy Genetic Algorithms (Halhal et al., 1997), Shuffled Complex Evolution (SCE)

(Duan et al., 1992), Simplex based Evolutionary Algorithms (sEA) (Muttil and Liong, 2002), Simulated Annealing (SA) (Cunha and Sousa, 1999), Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995), Shuffled Frog Leaping Algorithm (SFLA) (Eusuff and Lansey, 2003), Ant Colony Optimization Algorithms (ACOAs) (Dorigo et al., 1996), GLOBE (Abebe and Solomatine, 1998), etc.

1.2 SCOPE OF THE STUDY

Deriving at an optimal design of pipe sizes and some parameters of water distribution network model has been problematic to the water engineers. Instead of using the cumbersome and computationally long trial-and-error approach, a family of population-evolution based search algorithms known as evolutionary algorithms (EAs) has been extensively considered in the field of water distribution network modeling. However, very few of the algorithms have received widespread acceptance in the commercial applications. This is because most algorithms require high number of function evaluation and computational time to solve even a simple problem. The present study modifies and applies an evolutionary algorithm to increase its robustness in obtaining the optimal decision variables of water distribution network.

1.3 OBJECTIVES OF THE STUDY

This study uses an evolutionary algorithm, Shuffled Complex Evolution (SCE) in the field of water distribution network modeling. It is noteworthy that in 1992 Duan et al. developed SCE to construct an optimization model based on Nelder and Mead simplex search method. The method is used to calibrate Conceptual Rainfall-Runoff model. Later, Kuczera (1997), Gan and Biftu (1996), Eckhardt and Arnold (2001), and Thyer et al. (1999), showed the robustness of SCE in the various applications.

The aim of this study is to explore and enhance the applicability of SCE in water distribution network modeling. The main objectives are as follows:

1. To propose and apply a robust algorithm, Shuffled Complex Evolution (SCE), to optimize the design of water distribution network. SCE is coupled with a hydraulic network solver EPANET that deals with both steady-state and extended period simulation;
2. To compare the performance of SCE with other widely used optimization algorithms (e.g. GA) on several cases demonstrated in journals;
3. To apply the coupled models in the design of a real water distribution network;
4. To apply Kohonen Neural Network to improve the search capability of the SCE algorithm especially in the design of high dimensional design problems;
5. To rehabilitate an existing water distribution network. The coupled models are applied to choose the optimal rehabilitation options (replacing, cleaning, or paralleling the existing pipes) of the network; and
6. To demonstrate the use of SCE to the calibration of water distribution network model. The network parameters such as pipe roughness coefficients and/or nodal demands are determined using the coupled models (SCE-EPANET).

1.4 ORGANIZATION OF THE THESIS

Chapter 2 describes the previous research works in the water distribution modeling and the problems associated with the use of evolutionary algorithms to optimize the design of water supply systems. The fundamental of Kohonen Neural Network, applied to enhance the global optimum search capability of SCE, is also presented in this chapter. Determination of pipe roughness coefficients and nodal demands by calibrating a water distribution network model are discussed as well.

EPANET network solver and Shuffled Complex Evolution (SCE) are described in details in Chapter 3. The linking procedure between SCE and EPANET is also presented in this chapter.

Chapter 4 demonstrates the application of the proposed model consisting of evolutionary algorithms (SCE) and EPANET in the design of new as well as existing water distribution network. The performance of SCE is compared with GA and other algorithms in designing three new networks and in rehabilitating one existing network.

The application of the coupled models described in Chapter 3 to calibrate water distribution network model is presented in Chapter 5. Network parameters' values must be pre-specified in the analysis, design and rehabilitation of water distribution network. However, some parameters' values like pipe roughness coefficients of aging pipes are difficult to assess. A method called calibration to determine the value of these parameters is discussed in this chapter.

Finally, the conclusions reached in the present study and the recommendations for further research are given in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

A well planned water distribution network is very essential in the development of urban areas. The network is built to satisfy various consumer demands while meeting minimum pressure requirements at certain nodes. In the design stage it is of interest to arrive at the least-cost solutions that satisfy a set of constraints including demand and pressure requirements. Often it is also of interest to arrive at less expensive solutions that, however, violate slightly the constraints. Accordingly, research interests have been concentrating on the development of efficient evolutionary algorithms (optimization techniques) to search for the optimal combination of decision variables (e.g. pipe diameters) from a large number of solutions.

In this chapter, various techniques known in the design of water distribution network are first reviewed. Review on some recently emerging evolutionary algorithms useful to solve complex non-convex problems is also presented. This is followed by a review of fundamentals of Kohonen Neural Network which is incorporated in this study to enhance the effectiveness of a selected evolutionary algorithm. Finally, a review on calibration of water distribution network model using evolutionary algorithms is also conducted.

2.2 TECHNIQUES IN WATER DISTRIBUTION NETWORK DESIGN

2.2.1 Conventional Techniques

In the design and analysis of water distribution systems, the conventional procedure uses a trial-and-error approach. The performance depends upon the users' intuition, experience, skill, and knowledge. However, this approach is inefficient particularly in the design and analysis of large complex system. As an example, to determine the least-cost water distribution network would require a selection of pipe sizes available in the market. Thus, a large number of repetitive simulations is required to arrive at a satisfactory network.

2.2.2 Traditional Optimization Techniques

Several optimization techniques, instead of the trial-and-error approach, have been used in the design of new as well as expansion of existing water distribution networks. These traditional optimization techniques include linear, non-linear and dynamic programming.

2.2.2.1 Linear Programming

Alperovits and Shamir (1977) first presented a linear programming gradient (LPG) method in the optimal design of water distribution network. To apply LPG, they linearized the mathematical formulation. Segmental lengths of the pipe with different diameters were used as decision making variables. The objective function was to minimize the cost of the total pipe lengths. However, it is not desirable to have pipes that constantly change size along the network. Such pipe arrangement causes bottleneck in the system when the flow direction changes (Walski et al., 1990). The LPG method is later improved by a number of researchers (Quindry et al., 1981;

Morgan and Glulter, 1985; Fujiwara et al., 1987; Kessler and Shamir, 1989; Fujiwara and Khang, 1990; and Eiger et al., 1994). The improved approaches used iterative processes. Flow rates or pressure heads are fixed and the pipe sizes are optimized for the specified flow and pressure requirement. Morgan and Glulter (1985) considered multiple demand patterns in their work. They adapted a linear programming model with a Hardy-Cross network solver to design water supply systems. Kessler and Shamir (1989) presented a two-stage linear programming gradient (LPG) method. In the first stage, for a given set of flows, several sets of heads are determined by LP. In the second step, flows are modified according to gradient of the objective functions. Eiger et al. (1994) later used the same formulation of Kessler and Shamir (1989). They solved the problem using a non-smooth branch and bound algorithms, and duality theory. The algorithms are a combination of primal and dual processes and stopped when the gap between the best solution and the global lower bound is within a prescribed tolerance. The LP model suffers losses in the process because of linearization of non-linear real problems. It is not always convenient to linearize the problem and in some cases, it may disrupt the solution of the original problem.

2.2.2.2 Non-Linear Programming

A non-linear programming technique (NLP) was developed by Chiplunkar et al. (1986). Su et al. (1987); Lansey and Mays (1989); and Duan et al. (1990) applied NLP for the design optimization of water distribution systems. Compared to LP, NLP model can deal with multiple demand pattern and much higher number of design variables. Chiplunkar et al. (1986) used Davidon-Fletcher-Powell method and incorporated graph-theoretic approach with Newton's method. However, in NLP technique, the loop flows are assigned as the optimal variable set which is searched for minimizing the cost of the systems. One of the problems reported is that a looped network often becomes a tree network with several zero value in some pipe diameters. Moreover, they found that the NLP model often converged prematurely to the local minima. Su et al. (1987) used NLP that was based on the generalized reduced gradient (GRG) technique and a steady-state simulation model to design the optimal control variables. Lansey and Mays (1989) determined the decision variables by using the same NLP optimizer and a hydraulic network simulation model, KYPIPE (Wood, 1980).

In the last few decades, non-linear programming algorithms have become one of the most widely used methods for solving water distribution network problems. The most efficient of these methods are gradient based algorithms that require at least the first order derivatives of both objective and constraint functions; these are needed to define the appropriate search direction. Gradient based techniques can easily identify a relative optimum closest to the optimum design. However, these methods do not guarantee the global optimal solution if the design space is non-convex. It is also inadequate in problems where the design space is discontinuous, as the derivative of both the objective function and the constraints may become singular across the boundary of discontinuity. In addition, the pipe diameters considered in NLP are continuous that may not match the available commercial pipe sizes and require rounding up of the final solution. This rounding up of the solution destroys the quality of the optimal solution, even may not guarantee a feasible solution (Savic and Walters, 1997; Gupta et al., 1999; Cunha and Sousa, 1999; Simpson et al., 1994). NLP also cannot handle large water distribution network. Recently, NLP is not accepted widely in the optimization field.

2.2.2.3 Dynamic Programming

Since 1960s, Dynamic Programming (DP) (Wong and Larson, 1968), a mathematical technique, has been adapted in various optimization problems related to water resources engineering and management. It solves complex optimization problems by dividing it into a series of sub-problems. This sub-problem is referred to as stage. DP is applied to the problems where each stage is related to the previous stage. The output state of a stage is taken as the input state of the following stage. Dynamic Programming can be used to pipe network optimization of tree like water distribution network where a stage is the design pipeline between the nodes and state represents the head of a node. The decisions made at each stage produce a return cost that is used to calculate the cost of the network. It can handle more general form of cost function which in turn depends on pipe pressure as well as pipe diameters.

Vamvakeridou-Lyroudia (1993) presented a two-stage dynamic programming approach together with a heuristic algorithm. In the first stage, pipe sizes were initialized by a heuristic technique. In the second stage, DP was applied to iteratively calculate the optimal solution. At each stage, Newton-Raphson network simulation model was used. They developed LOOPOPT based on above mentioned techniques to solve looped, branched or mixed type of water distribution network problems.

A dynamic programming based optimizer (GPO) was developed by Lall and Percell (1990) in the gas transmission pipeline systems. As an optimization tool, it was used to determine the feasible steady state strategy in the operation of compressor stations satisfying several constraints to minimize the overall fuel cost of operating the pipeline. However, the application of dynamic programming was limited to simple network systems. They observed that if the system increases in size, the computational time required to solve the optimal strategy becomes very large, a case of "the curse of dimensionality".

2.2.3 Heuristic Optimization Techniques

Gessler (1985) and Loubser and Gessler (1993) applied enumeration approach to the design and to the rehabilitation of water distribution network. In the enumeration technique, the modeler assigns search space by specifying a range of commercial diameters for each pipe in the network. The algorithm considers all possible combinations of pipe diameters, and check each combination whether the pressure constraints are satisfied. Eventually, the algorithms select the combination of pipes with the least cost. This optimal combination, of course, meets the specified constraints. This algorithm removes some complexities. However the most important drawback is that extensive computational time is required to find even a suboptimal solution. This is because the individual pipe is sized based on the discrete available sizes in the market, and the whole set of possible combination of decision options contains some inferior solutions. Checking all of these solutions will require high computational time.

The discrete nature of the decision variables (diameter of the pipes) restricts the search to a finite number of possible diameters. However, in practice this number is very large for large networks. Evaluation of each possible design is impractical for most of the problems. The evaluation of certain designs using evolutionary algorithms makes this an acceptable approach. Recently, researchers focus on the use of meta-heuristic techniques to evaluate certain network designs. These search techniques normally solve the unconstrained optimization problem and select the pipe diameters (design variables) within prescribed ranges. As a result, the design constraints are satisfied automatically. Heuristic optimization technique works with a network solver that handles the hydraulic relationships and the constraints. If the hydraulic requirements are not satisfied, the objective function is modified by adding a high numerical value or a penalty term to stop searching near this point or along this direction (Savic and Walters, 1997).

The presently used meta-heuristic approaches include genetic algorithms (Goldberg and Kuo, 1987; Simpson et al., 1994; Savic and Walters 1997; Dandy et al. 1996; Gupta et al., 1999; Wu and Simpson, 2001), simulated annealing (Cunha, and Sousa, 1999), shuffled frog leafing algorithms (Eusuff and Lansey, 2003), ant colony optimization algorithms (Maier et al., 2003) which deal with the population of points simultaneously in the search for a global optimum. Search strategy, which is based on the objective function, improves the quality of the solution through some evolutionary processes.

Simpson et al. (1994) used simple genetic algorithms in which each individual population is represented in a string of bits with identical length that encodes one possible solution. All binary coded population of points (chromosomes) undergoes three operations: selection, crossover and mutation. The simple GA uses roulette wheel selection, one-point crossover and bit wise mutation to determine the optimal network design. A steady-state network solver is used to compute the hydraulic performance of each of the network in the population. If the network is not sufficient enough to meet the head constraints, the deficiencies are incorporated into the objective function (network cost) as penalties to calculate the total cost of the network.

Hence, the quality of each solution is evaluated using a fitness function which is the inverse of the total network cost. The performance of GA is compared with the complete enumeration and non-linear programming optimization techniques on a typical problem. Simpson et al. (1994) found that GA obtained global solution in a relatively few number of function evaluations.

The simple GA was improved by Dandy et al. (1996) using the concept of variable power scaling of the fitness function, an adjacency mutation operator, and gray codes. The power of the fitness (inverse of the objective function value) is allowed to increase in steps as the GA run develops. A low value of exponent is employed at the start of GA which preserves some population diversity and global exploration of the solution space in the early generation. A high value of exponent is needed to accentuate the small differences in the string fitness. In addition, they introduced creeping or adjacency mutation operator with commonly used bitwise mutation operator. The adjacency mutation operator is applied to a randomly selected complete decision variable from the coded string. This operator mutates the selected decision variable substring to an adjacent decision variable substring up or down the list of design variables choices. Finally, instead of binary codes, Gray codes are used to represent the design variables. Due to provision of these new features, Dandy et al. (1996) concluded that the improved GA performed better than simple GA. They also argued that the improved GA performed better than linear, non-linear, dynamic programming methods and an enumerative search method.

Savic and Walters (1997) also used standard GA in conjunction with EPANET network solver. They developed a computer model GANET to design least-cost pipe network. In GANET, the standard GA which is based on the natural genetic use binary alphabet to generate the chromosomes like those found in DNA. The chromosomes which represent a particular solution of the problem improve their quality through several genetic operators. GANET is user friendly where the input requirements are the same as the input of the hydraulic simulation models in addition to the genetic algorithmic parameters. The capability of GANET for design optimization was demonstrated on three problems.

To improve the capacity of GANET, Geographical Information Systems (GIS) (StruMap), together with a network solver (HARP), a relational database and an object oriented genetic algorithm library were integrated (Atkinson et al., 1998). The resulting package is designed for use with a wide range of optimization problems related to water systems managements, like network design, rehabilitation and calibration problems.

Gupta et al. (1999) applied GA with a hydraulic simulator ANALIS (Bassin et al., 1992) which was based on the graph theory to assess the hydraulic performance of the network design. The result obtained was compared with NLP technique. They found that though NLP converged very rapidly, GA provided better solutions. Although the quality of the final solution was improved, they needed considerable computational effort to arrive at the least network cost.

All the methods described above use simple binary or gray coded GA to represent the pipe diameters (design variables). These coding schemes sometimes produce redundant states (decoded value may not belong to the domain of the parameters) that do not represent any of the pipe diameters and hamming cliff (Vairavamoorthy and Ali, 2000). The problem of hamming cliff occurs when the binary code of two adjacent values differs in each one of their bits; the convergence towards the global optima may not be achieved under this condition. Vairavamoorthy and Ali (2000) handled these problems by incorporating real coding to the variables and linear transfer function model to avoid the need for a hydraulic network solver. Their proposed model was tested on several benchmark problems and proved the efficiency compared to simple GA based methods.

An improved version of GA, called multi-objective structured messy genetic algorithms (SMGA), is proposed by Halhal et al. (1997) and Walters et al. (1999). In SMGA, a flexible coding with variable string length is used to represent the population of points. This algorithm follows a progressive evolutionary process in which the initial selected short string lengths of the solutions are allowed to increase through the process of concatenation in subsequent generation with the improvement of the quality of the points. The SMGA has two major advantages over standard genetic algorithm (SGA): (1) it encodes only small number of relevant decision variables having small string length, whereas, SGA encodes all decision variable even though some of them do not need to upgrade; and (2) since SMGA does not consider all decision variables, the computational time to reach the optimal or near optimal solution is lower than SGA.

Wu and Simpson (2001) and Wu et al. (2001) also reported single objective first messy genetic algorithm (fmGA) in the design of water distribution systems. The first messy GA solves the water distribution network problem using two loops, namely, inner loop and outer loop. The outer loop initializes a large population size of random variables. The inner loop consists of a building block filtering phase and juxtapositional phase. The building block filtering phase filters all strings of the population to select the better-fit short strings and also reduces the string length. And the juxtapositional phase produces new string of the population using common genetic operators (selection and reproduction) to move towards optimal solution. Finally, fmGA produced reasonable results in the typical benchmark problems.

Instead of using a single optimization algorithm, Abebe and Solomatine (1998) applied GLOBE (Solomatine, 1995) that comprises several search algorithms including GA. They identified that very few algorithms reach to optimal or near optimal solutions. Cunha and Sousa (1999) introduced a random search algorithm (Simulated Annealing) that is based on the analogy with the physical annealing process with Newton search method to solve the network equation.

Todini (2000) presented a new technique for designing water distribution network based upon resilience index to improve the reliability and the availability of water during failure conditions. In this technique, the resilience concept is used to develop a heuristic optimization approach which deals with cost versus resilience space, the edge of the non-dominated solutions or the Pareto set. The proposed technique was tested on a large water distribution network.

Vamvakeridou-Lyroudia (2001) developed G_FUZNET which is a combination of fuzziness and GAs to design the network. They evaluated total aggregated membership functions for each possible solution. There were three stages of aggregation: (1) aggregation for each node- pressure constraints for the nodes are aggregated; (2) aggregation for each link- partial membership functions for velocity constraints for links are aggregated; and (3) pressure aggregator for all nodes- total pressure aggregator is applied to evaluate the total member ship function of the system.

Eusuff and Lansey (2003) proposed shuffled frog leaping algorithm (SFLA), a meta-heuristic algorithm, which is based on memetic evolution (transformation of frogs) and information exchange among the population. Frogs which are the hosts of memes (consist of memotype like gene in chromosome in genetic algorithms) search the particle with highest amount of food in a swamp by improving their memes. Improvement of memes occurs by sharing information among frogs. Alternatively, memes which represent the coordinate of frogs can change their position through the adjustment of the memotype. Frog leaping improves their memetic performance using the process involved in particle swarm optimization (PSO) in a subset of virtual frogs (memplex). The memplexes are finally shuffled to move towards the global optimum. They got the optimal and near optimal solution with the expense of higher computational time.

Maier et al. (2003) used an evolutionary algorithm, i.e. ant colony optimization algorithms (ACOAs) which works on the basis of foraging behavior of the ants. In the design of water distribution network, decision points are chosen from available pipe diameters. These choices depend on certain characteristics of the ant and heuristic values. Heuristic value is the inverse of the total cost of each choice. The ant characteristics are changed in such a way that favors the choice results in smaller network cost. Similarly, the characteristic are decreased if the choice of the network does not satisfy the pressure constraints. The details of ACOAs are presented later in Section 2.3.3.

In the solution method by heuristic optimization technique, the feasibility of the individual member depends on the degree of constraint violation or the distance away from the feasible region which is accounted using a penalty function. Penalty function accounts mainly nodal pressure deficit in water distribution network design. It is proportional to the maximum pressure deficit (maximum difference between the required head and the simulated head at each head) multiplied by a penalty factor. Most of the methods consider only the maximum pressure violation and ignore the importance of degree of violation at other nodes. If the maximum pressure deficits are the same, equal penalties will be assigned for those designs where the majority of the nodes violate their pressure constraints and those designs where only a few number of nodes are in pressure violation (Vairavamoorthy and Ali, 2000). Moreover, the penalty factor in the function is very important and needs to be tuned to obtain optimal results efficiently. If the penalty factor is too low, many infeasible solutions will dominate the algorithmic population. If the penalty factor is very high, good solutions that have just failed will be eliminated permanently in the search process (Wu and Simpson, 2002). The usual methods use trial and error approach to select appropriate penalty coefficients and the fixed penalty factor is used in every run regardless of the degree of pressure violation and number of demand nodes at which pressure is less than minimum requirement. Vairavamoorthy and Ali (2000) proposed to consider variable penalty factor based on the degree of violation. They summed the pressure deficit at all nodes where the nodal pressure failed to meet the minimum requirement. Eusuff and Lansey (2003) also followed the same approach to calculate the penalty cost.

Vamvakeridou-Lyroudia (2001) suggested fuzzy reasoning for constraints handling and feasibility checks. Instead of penalty functions, he used total aggregated membership function to the set of feasible solutions. A non-linear S-shaped membership function was employed. Three constraints in form of diameter, velocity and pressure constraints were introduced. The membership functions for each of these constraints were incorporated to add with actual real network cost.

Wu and Simpson (2002) introduced an approach called the self-adaptive boundary search strategy in a fast messy Genetic Algorithms to overcome the trial selection approach of the penalty coefficients. The method adapts and co-evolves the penalty factor to search the boundary of the feasible and infeasible region.

2.3 EVOLUTIONARY ALGORITHMS

Evolutionary Algorithms are stochastic methods that mimic the evolutionary processes in nature**.** They are efficient global search and optimization techniques in the fields of engineering and computer science, solving complex engineering problems. They explore search space by incorporating a population of potential solutions applying the principle of survival of the fittest to produce better approximations to a solution. Initially a number of individuals are generated randomly. The objective function is then evaluated for these individuals. The first generation is produced. After one generation, if the termination criteria are not met, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the feasible domain. This process evolves the children (offspring) that are better suited to their environment than the parents. The fitness of the offspring are then evaluated and put back into the population**.** EAs model follow the cycle such as evaluation, selection, and reproduction. This cycle is terminated either when solution with error of an acceptable level is found or a predetermined limit on the number of generation is reached.

The model uses elitism, where the best individual in the current generation is kept for the next generation that ensures information sharing. This information guides the search engine from being trapped in the infeasible region and guarantees that the best solution in one generation is at least identical to that of the previous generation. Figure 2.1 shows the flow chart of an Evolutionary Algorithm.

Evolutionary Algorithms (EAs) include Genetic Algorithm (GA), Simulated Annealing and many others which will be discussed in the next section.

2.3.1 Genetic Algorithms

Genetic Algorithm (GA) was proposed by Holland (1975) and further developed by Goldberg (1989). GA, a highly dimensional stochastic optimization algorithms mimic the natural biological processes based on Darwinian survival-of-the-fittest philosophy. This mathematical model is adapted to design and analysis of engineering problems such as design of water supply systems, calibration of water distribution network model.

GA performs searching through natural selection rules that guide the evolution process and exploit historical information to direct the randomized search towards the optimum. This algorithm is convenient for those problems in which the solution space is non convex with the existence of numerous local optima. GA explores a number of simultaneous searches in the most promising region and ultimately improves the aptitude of the population of points over generation.

In general, GA begins with a randomly generated initial decision vectors termed as population. With regard to water network design, each decision vector comprises of a set of decision variables that include pipe sizes of the network. Each decision variables in the decision vector is coded as a binary number. With this binary coding, the possible solution of a given problem is represented by a string of bits of finite lengths.

Perez and Joaquin (1995) described the string (solution of the problem) in GA as a chain consists of series links. The quality of the chain is represented by the objective function of the model. Each link takes the binary value of either 0 or 1. The decision variables of a network problem may contain a set of links (binary representation of a number). Each link carries a certain characteristics of the solution.

GA includes three fundamental genetic operations of selection, crossover and mutation. These operations are used to modify the chosen solutions and select the most appropriate offspring to pass on to succeeding generation.

2.3.1.1 Selection

Selection is a natural process, whereby individuals are selected according to their fitness. Good individuals will probably be selected several times in a generation; poor ones may not be selected at all.

Consider a two-dimensional problem in which the two variables can be represented by a 5 digit binary numbers which are as follows:

$X1$ = 01010

$X2$ = 10111

The binary representation for $X1$ and $X2$ can be placed head-to-tail to produce a ten digit number. Such several ten digit numbers constitute a population of the design. In the selection process, a subset of decision vectors is selected from this current set of population (decision vectors) based on the objective function value. After selecting this subgroup, a new set of decision vectors is created applying sequential operations of crossover and mutation. The crossover and mutation operations are carried out on a pair of strings from the selected decision vectors.

2.3.1.2 Crossover

Crossover transfers the genes of individuals to offspring. In applying single point crossover operation, one location is chosen at random along the strings and the corresponding binary numbers are interchanged at this location. Two binary strings are cut to produce two head segments and two tail segments. The tail segments are then interchanged to generate two new binary strings which are called offspring (child). An illustration of the crossover process between mating parents is shown in Figure 2.2.

2.3.1.3 Mutation

After cross-over of the parent population, a mutation operation is applied to each of the binary strings of the resulting offspring population. Mutation process randomly alters each gene and safeguards the genetic search against losing valuable genetic material in the crossover operation. Mutation process consists of changing the value of the binary bit randomly. If the value of link is zero, it is changed to 1 and vice versa. The application of mutation process is necessary because the value of the links may not be changed in the selection and crossing phase. As a result, the search may be confined to a small portion of the solution space and lost diversity. Mutation can avoid solutions from being confined in local optima. The probability that a particular string will be mutated is very small. Figure 2.3 shows the operation of mutation on a typical string of bits.

2.3.2 Simulated Annealing

Simulated annealing (SA) (Metrpolis et al., 1953; Kirkpatrick et al., 1983) has been efficiently used in solving combinatorial problems. This method performs on the basis of the thermal process that represents the way of cooling and annealing of solids. The temperature of the solid molecules is increased to a maximum value at which it melts and gets mobility. At this stage, the atoms in the solid molecules have high energies to arrange themselves. Later, the temperature of the melted solid is decreased slowly to form crystalline structure. If the cooling is carried out rapidly, irregularities are found in the crystal structure. Suppose, the current energy state i of the solid with energy E_i is changed to the state j with energy E_j applying a perturbation mechanism. The later state j will be the new current state if the energy difference $(E_j - E_i)$ is less than or equal to zero. Otherwise, if the energy difference is greater than zero, the state j will be accepted with a probability of [exp $(E_i - E_j)/K_B*T$]; where, K_B is Boltzmann constant; T denotes temperature.

The SA algorithm search is based on four principals (Pham and Karaboga, 2000) which are: (1) representation of solutions; (2) definition of cost function; (3)

definition of the generation mechanism for the neighbors; and (4) designing a cooling schedule. Hence, the states of the solid represent feasible solutions and the energies of the state correspond to the objective function values (cost). The current feasible solution is randomly changed to the new solution in the neighborhood of the current solution according to the Metropolis's criterion. The new solution will be accepted as the current solution if the change in the objective function value of the two solutions is negative. Otherwise, it is accepted based on Boltzman's probability defined earlier. Finally, the algorithm approaches the global optima by controlling the parameters of initial temperature, a temperature update rule, the number of iterations to be performed at each temperature step and a stopping criterion for the search.

2.3.3 Other Algorithms

Besides GA and SA, there are many other meta-heuristic algorithms available in the optimization field. The common algorithms of this category are Ant Colony Optimization Algorithms (ACOAs), Particle Swarm Optimization (PSO), and Shuffled Frog Leaping Algorithm (SFLA).

ACOAs (Dorigo et al., 1996) is an adaptive meta-heuristic optimization method inspired by nature which includes simulated annealing, genetic algorithms and tabu search. ACOAs incorporates the behavior of real ants. The behavior of ant is to establish shortest paths from the nest to food sources without strength of vision. During this searching of the shortest paths, the individual ant communicates with each other by the pheromone trails. The pheromone trails are dissipated on the path taken indicate the distance and quality of the food source. As other ants observe the pheromone trail, they are attracted to follow it. The path is marked again, reinforced and will attract even more ants to follow the trail. Therefore, efficient trails increase their pheromone level over time while poor ones reduce to nil. Based on this behavior of the real ants, Dorigo et al. (1996) implemented following analogies: (1) artificial ants scan the solution space while real ants search their natural environment for food; (2) the objective function values represent a mapping of the food sources quality and an adaptive memory is equivalent to the pheromone trails. Artificial ants are equipped with a heuristic function in order to support their search through the set of feasible solutions.

Particle Swarm Optimization (PSO) is a population based heuristic search technique proposed by Kennedy and Eberhart (1995). Though, PSO has some similarities with EA, it simulates the behavior of a bird flock, where social sharing of information takes place. Individuals profit from the discoveries and previous experience of all other companions during the search for food. The behavior of each individual is affected either by the best local or by the best global individual to help it flying through a hyperspace. Moreover, an individual can learn from its past experiences to adjust its flying speed and direction. Therefore, by observing the behavior of the flock and memorizing their flying histories, all the individuals in the swarm can quickly converge to near-optimal.

Based on the PSO and the shuffling concepts in SCE, described later in Chapter 3, Eusuff and Lansey (2003) proposed the Shuffled Frog Leaping Algorithms (SFLA).

2.4 KOHONEN NEURAL NETWORK

Kohonen neural network (Kohonen, 1989) which is very popular for pattern recognition was developed to extract representative points from the input data. A

Kohonen's self organizing map (SOM) performs unsupervised learning to discover underlying structure of the data. It is sometimes represented as topology-preserving map. A topological map keeps neighborhood relations to organize the data points. Kohonen self organizing map transforms M dimensional input signal vector into one or two dimensional discrete map. This is performed in a topologically ordered fashion. It classifies the input data into different patterns and allocates similar input vector in one class based on the minimum Euclidian distance.

The structure of Kohonen neural network consists of two layers, namely input and output layers (Figure 2.4). The number of neurons in input layer usually represents the dimension of the input vector. The number of neurons in output layer corresponds to the user defined number of groups that the input data will be clustered into, N (for example). The input pattern is fed to each output unit. Each neuron in the output layer is connected to all of the neurons in the input layer by a weight vector. That means, the input lines to each output unit are weighted. These weights are initialized to small random numbers. For example, the weight vector of the j^{th} output neuron would be:

$$W_j = W_{ji}\ ; \qquad i = 1,2,3,4,\ldots\ldots\ldots\ldots,M \tag{2.1}$$

where M is the number of input neurons or dimension of the input vector.

The output neurons also keep interactions with all the existing neurons within the distance (neighborhood) (Figure 2.4) of $\Lambda_j(t)$. The weight vectors associated with the output neurons within $\Lambda_j(t)$ are updated through unsupervised learning.

Kohonen neural network learns to solve a problem and modifies the values of the weighted connections through unsupervised training. The unsupervised training paradigm attempts to identify relationships inherent in the data without the knowledge of the outputs.

The brief description of the unsupervised learning process is given below:

- Initialize the weights for each output unit: Small values are assigned to the weight vectors. The neighborhood and learning rate are also initialized.
- Apply an input vector X to the network: An input vector is selected randomly and fed it to the network.
- Find the winning output unit: Calculate the distance D_j between X and the weight vector W_j of each output neuron. The distance between input vector X and each output neuron's Weight $W_j\,(n)$ at time n can be represented:

  $$D_j = \| X - W_j \| \; ; \qquad j = 1,2,\ldots,N \tag{2.2}$$

  where $\| \,.\, \|$ is Euclidean norm.
- The neuron that has the weight vector closest to X is declared as the winner. And the weight vector W_c of the winner is used as the center of a group of weight vectors.
- Adjust the weight vectors of all neurons within the neighborhood of the wining neuron through:

$$W_j(n+1) = \begin{cases} W_j(n) + \eta(n)[X(n) - W_j(n)] & if \quad j \in \Lambda_c \\ W_n(n) & otherwise \end{cases} \tag{2.3}$$

where $\eta(n)$ is the learning rate parameter, and Λ_c is the neighborhood function centered on the winning neuron C.

- Reduce the size of neighborhoods if required.
- Perform the above steps for each input vector until the specified number of iterations is achieved.

In this study, the representative points (winning neurons), determined after clustering using SOM, are introduced as the initial points in the evolutionary algorithms (EAs). Consequently, the robustness of the EAs increases significantly. This is shown later in Chapter 4.

2.5 WATER DISTRIBUTION NETWORK MODEL CALIBRATION

A hydraulic network model calibration is necessary to take into account the physical changes that may occur in the network. Calibration includes the determination of network parameters (pipe roughness coefficients and nodal demands). The parameters are often not exactly known and very much sensitive to the age of the pipe which necessitates periodical measurement for optimal management of water delivery systems. Therefore, the parameters are determined through model calibration. Since the manual calibration is very time consuming and tedious, an automatic calibration technique is used. In the calibration process, the parameters are adjusted so that the simulated pressure, pipe flow and tank level mimic the measured field value. Several studies (Ormsbee, 1989; Lansey and Basnet, 1991; Ferreri et al., 1994; Lingireddy and Ormsbee, 1998; Vitkovsky et al., 2000; Lingireddy and Ormsbee, 2002) have been carried out to establish an automatic calibration scheme. The main aim is to develop a robust, efficient and reliable automatic procedure that maintains close resemblance between the model output and the field results.

In the calibration process, the objective function is formulated as a nonlinear function subject to different linear and nonlinear equality and inequality constraints. Ormsbee and Lingireddy (1997) illustrated seven steps involved in model calibration such as identification of the intended use of model, determination of initial parameters, collection of calibration data, evaluation of results, macro-level calibration, sensitivity analysis and micro-level calibration. The micro-level calibration is subdivided into steady-state and extended period calibration. Steady-state calibration involves the adjustment of parameters to match pressure and flow rate for static loading condition. However, the extended period calibration involves the adjustment of parameters to match pressure, flow and tank level for dynamic loading conditions.

Ormsbee (1989) and Lingireddy and Ormsbee (2002) proposed to use the nodal pressure, pipe flow and tank water level for the calibration of water networks at different demand loading conditions. Walters et al. (1998) calibrated water distribution network model using genetic algorithms. They used the objective function which calculated the root mean square of the absolute errors of all flows and pressures measurements over 24 hours period.

Artificial neural network (ANN) in conjunction with genetic algorithms was used by Lingireddy and Ormsbee (1998) for reducing the computational effort. The optimization model which is based on genetic algorithms uses ANN for function evaluation. Genetic algorithms provide the data sets for training the neural networks. Later on, the trained ANN can be used as a simulation tool for evaluating the hydraulic characteristics. ANN works similar to the biological processes of brain. It is an interconnected system and comprised of a set of simple processing units in which some elementary calculations are carried out. These processing units (nodes) are organized into different layers such as input, output and hidden layers. For a sequential set of input, it arranges itself internally to produce the known output. The output of a well trained neural network does not deviate much from the actual output.

For large water distribution network, the use of Neural Network in place of simulation tool (network solver) can significantly increase the computational efficiency of the optimization model.

Greco and Giudice (1999) presented a nonlinear optimization algorithm along with a standard, off-the-shelf, network solver for model calibration. They formulated a nonlinear optimization problem and used an objective function that was to minimize the sum of square differences between simulated and initial assumed roughness under a set of constraints to ensure identical pressure results found from the model and in the field.

Liggett and Chen (1994) introduced inverse transient method (ITM) for the determination of friction factors. This method was further improved by Simpson and Vitkovsky (1997) and Vitkovsky et al. (2000). Vitkovsky et al. (2000) and Simpson et al. (2000) used genetic algorithms to enhance the process. In a pipe system, transient is normally taken place when pressure variance and the flow velocity is generated by a disturbance. The disturbance generates the waves propagate throughout the network. The network information is collected during propagating water hammer waves. ITM offers much potential in comparison to steady-state calibration techniques. Instead of using Levenberg-Marquardt method or any derivative based technique, the genetic algorithms with the inverse transient method were used successfully to calibrate the roughness coefficients of the pipes.

The solution process of the calibration problem is quite complex and the dependency of final results on the precise input data and other facts impose more difficulty to the model. To overcome these difficulties, a number of simplifications are made in the formulation. Though the problem is solved through simplification of the mathematical formulation, the above mentioned methods still need significant computational effort to produce reasonable results.

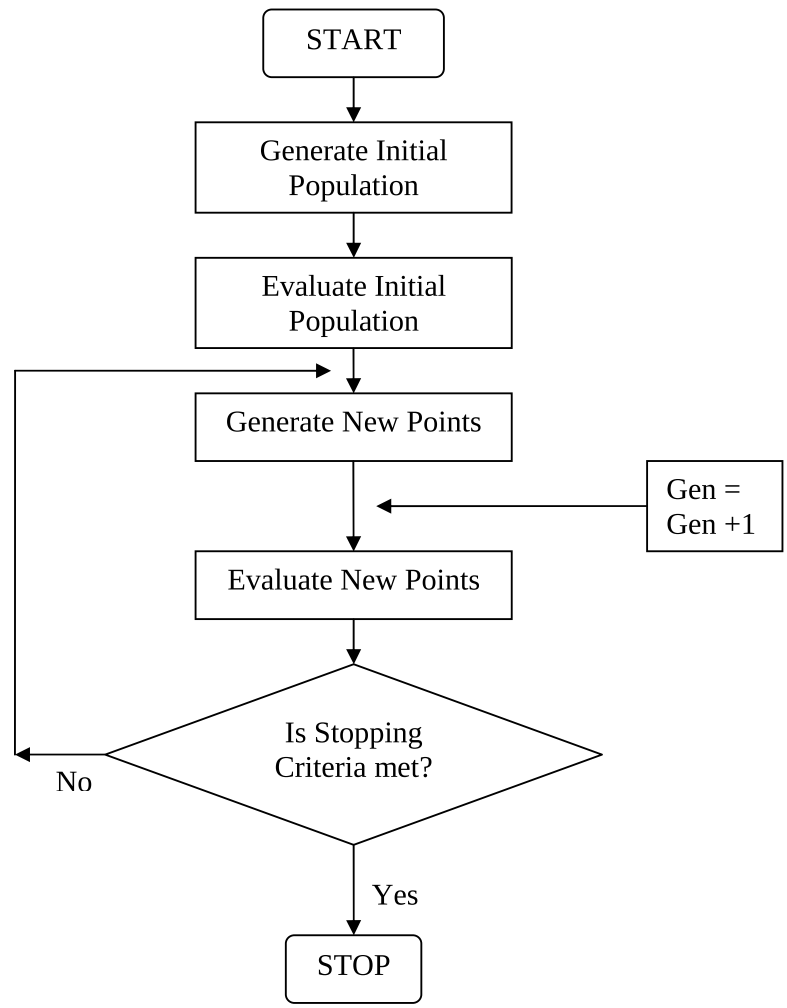

Figure 2.1 Flow Chart of Evolutionary Algorithm

	Crossover Point	**Crossover Point**
Parents	**010101| 0111**	**110111| 0101**
Child	**010101| 0101**	**110111| 0111**

Figure 2.2 Illustration of Crossover Operation

	Location for Mutation
Offspring	**0101010101**
Binary string after mutation	**0101000101**

Figure 2.3 Illustration of Mutation Operation

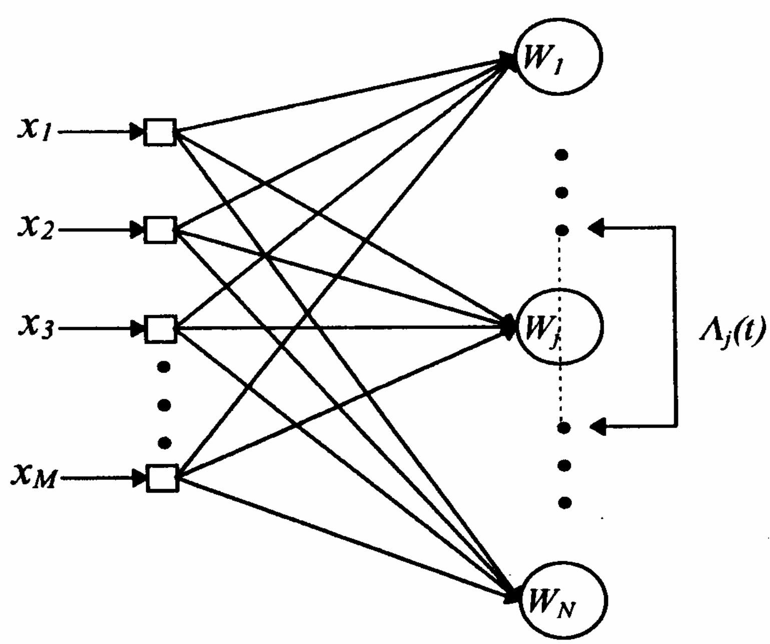

Figure 2.4 The Kohonen Network Architecture

CHAPTER 3

PROPOSED SCHEME

3.1 INTRODUCTION

Design of a reliable and cost-effective pipe network for water distribution systems is of great importance. The study aims to introduce a scheme for designing and rehabilitating water supply network. The model consists of an optimization algorithms and a network solver. An efficient optimization algorithm, Shuffled Complex Evolution (SCE), together with a network solver EPANET is used to arrive at the proposed scheme. SCE is chosen in this study because it searches in all direction based on Nelder and Mead simplex search techniques resulting little chance of getting trapped in local optima. EPANET is chosen because it handles both steady state and extended period simulation of water distribution network. In addition, this tool also can be used to perform water quality modeling. This chapter presents discussions on EPANET simulation model, the overall working mechanism of Shuffled Complex, Nelder and Mead local search technique, SCE algorithmic parameter selection, stopping criteria for the algorithm, exploration and exploitation capability. The proposed scheme and linking procedure between SCE and EPANET are described later on. Finally, the chapter ends with overall concluding remarks.

3.2 EPANET SIMULATION TOOL

EPANET (Rossman, 1993) is a public-domain, water distribution system modeling package developed by the U.S. Environmental Protection Agency's Water Supply and Water Resources Division. It performs both steady-state and extended period simulation (EPS) of a water distribution network. As discussed in Chapter 1, steady-state provides the state of the systems. For example, water engineers are interested to model only maximum-hour and minimum hour conditions. It computes hydraulic performance (pressures, flows, head-loss in the pipe) for a given layout and nodal demands. On the other hand, in extended period simulation, the system performance is evaluated for many consecutive time periods. Thus, it is assumed that the state of the network is constant within a certain time interval (1 hour for example). Nodal pressure, tank water levels, pipe flows, pump rates are determined on an hourly basis. EPS is required to understand the water usages (demand factor) over time, variation of tank water levels, or the pump operation over time.

EPANET applies coordinated approach to model both network hydraulics and water quality. The basic hydraulic equations involved in EPANET are briefly described below:

1. The flow equations in hydraulic model are governed by conservation of mass and energy. The law of mass conservation states that the rate of storage in a system is equal to the difference between the inflow and outflow to the system. For each junction, the conservation of mass can be expressed as:

   $$\sum Q_{in} - \sum Q_{out} = Q_{ext} \tag{3.1}$$

   where Q_{in} and Q_{out} are the inflows and outflows of the node; and Q_{ext} is the external demand.

2. Conservation of energy states that the difference in energy between two points is equal to the frictional and minor losses and the energy added to the flow component between these points. For each of the basic loops in the network the total loss can be written as:

$$\sum_{i,j \in I_P} h_{i,j} - \sum_{M_x \in J_P} P_E = 0 \tag{3.2}$$

where $h_{i,j}$ is the head loss in the pipe connecting nodes i and j; I_p is the set of pipes in the loop P; M_x refers to pumps; J_p is the set of pumps in the loop P; and P_E is the energy added by the pump M_x.

3. The head loss in the pipe is the difference between nodal head at both ends. If the Hazen-Williams equation is selected to calculate these head losses, then it would be:

$$\sum_{i,j \in I_p} h_{i,j} = \omega \frac{L_k}{C_k^{\beta_x} D_k^{\gamma}} Q_k \, |Q_k|^{\beta_x - 1} \tag{3.3}$$

where ω is numerical conversion constant; C is roughness coefficients; γ and β_x are regression coefficients; L_k, D_k and Q_k are length, diameter and flow of the kth pipe.

3.2.1 Modules of EPANET

EPANET consists of two modules. They are: (1) a network solver that performs hydraulic and water quality simulation; and (2) a graphical user interface (GUI) that serves as a front and back end for the network solver.

3.2.1.1 Network Solver Module

EPANET network solver module is a C-language computer program with separate code modules for input processing, hydraulic analysis, water quality analysis, linear equation analysis, and report generation. The input processor module receives a readable input file (.INP) written using a Problem Description Language (PDL).

The input file describes the network configuration where each network data is placed in a separate section identified by a keyword in brackets. Any line commencing with a semicolon is regarded as comment lines, and can be placed throughout the file. The properties of the network objects such as pipes, junctions, tanks, reservoirs, and pumps are entered in a columnar format to enhance the readability. A portion of a typical input file format is shown in Appendix A.1.

The hydraulic module performs a complete, extended-period hydraulic simulation and writes the results obtained at every time step to an external hydraulic file (.HYD). Water quality module computes substance transport and reaction throughout the network over each hydraulic time step, if a water quality simulation is called for by the input file. It writes water quality results to an unformatted output file (.OUT). If requested by the input file, a report writer module reads back the results of the computed simulation from the binary output file (.OUT) and conveys the results to a formatted report file (.RPT) that is useful and informative to the model users. The information in this file may be pipe flows, nodal pressures, heads etc. In the proposed model, an additional subroutine is added in report writer to extract the hydraulic heads which are passed to the optimization algorithm later on.

3.2.1.2 Graphical User Interface (GUI)

EPANET graphical user interface operates in Windows (95/98/NT) platform. It facilitates to construct the layout of the network to be simulated. The network can be drawn visually using point-and-click with the mouse and the network map provides a schematic layout of the distribution system. GUI is responsible for editing the properties of the network components and its simulation options. It calls the solver module to simulate the behavior of the network and accesses the results from the solver to display to the user in a variety of formats.

3.3 SHUFFLED COMPLEX EVOLUTION (SCE)

Shuffled Complex Evolution (SCE) is a global optimization tool developed at the University of Arizona (Duan et al., 1992). SCE has been applied for a variety of engineering problems by different researchers and it has been demonstrated that this algorithm is effective and efficient for a broad class of problems (Duan et al., 1992; Duan et al., 1993).

SCE (Thyer et al., 1999) works on the basis of four concepts: (1) combination of deterministic and probabilistic approaches; (2) systematic evolution of a complex of points; (2) competitive evolution; and (4) complex shuffling. The algorithm begins with a randomly selected population of points from the feasible space with the help of pseudo-random number generator and the sample of points is confined by lower and upper bounds of the parameter values. This random generation of points provides the potential for locating the global optimum without being biased by pre-specified points. The points are sorted in order of increasing criterion value so that the first point represents the smallest function value and the last point represents the largest function value. The randomly generated initial population is partitioned into several complexes of ($2N + 1$) points each, where N is the dimension of the optimization problem. Each complex is allowed to evolve independently to search the feasible domain in different direction. Each individual point in a complex has the potential to participate in the process of reproducing new points. From each complex, some points ($N + 1$) are selected to form a sub-complex, where the modified Nelder and Mead Simplex

Method (NMSM) is applied for global improvement. The points of higher fitness values have higher chance of getting selected to generate offspring. The NMSM performs reflection and inside contraction step to get a better fit point. This new offspring replaces the worst point of the simplex. The points in the evolved complexes are combined into a sample population. The sample population is sorted again, shuffled and reassigned into new complexes to enable information sharing. This process is repeated until some stopping criteria are satisfied.

A detailed description of the steps of the SCE (Duan et al., 1994) optimization algorithm is given below and illustrated in Figure 3.1:

1. Initialize number complexes (*p*) and number of points in each complex (*m*). Compute the sample size $S = p \times m$.
2. Generate *S* population of points randomly in the solution space ($\Omega \subset \Re^n$) using uniform probability distribution. Each of the *S* population represents a possible combination of *N* parameters ($x_1, x_2, \ldots\ldots\ldots, x_n$).
3. Compute the criterion value (f_i) at solutions (x_i).
4. Rank points: sort the *S* points in order of increasing function value and store them in an array $D = \{x_i, f_i, i=1, \ldots\ldots\ldots, S\}$, so that the first point ($i = 1$) represents the smallest criterion value and the last point ($i = S$) represents the largest criterion value.
5. Partition into complexes (Figure 3.3) – partition the *D* into *p* complexes ($A^1, \ldots, A^p$), each containing *m* points. The complexes are partitioned such that the first complex contains every $p(j–1)+1$ ranked point, the second complex contains every $p(j–1)+2$ ranked point, and so on, where $j = 1, 2, \ldots, m$. This can be expressed in mathematical form:

$$A^k = \{x_j^k, f_j^k \mid x_j^k = x_{k+p(j-1)}, f_j^k = f_{k+p(j-1)}\} \tag{3.4}$$

6. Evolve each complex: evolve each complex (A^k, $k = 1,\ldots\ldots,p$) according to the competitive complex evolution (CCE) algorithm which will be discussed in the next section.
7. Shuffle complexes: combine the points in the evolved complexes into a single sample population (replace $A^1, \ldots.,A^p$ into D); sort the sample population in order of increasing criterion value; shuffle (i.e. re-partition) the sample population into p complexes according to the procedure specified in Step 5.
8. Check convergence: if any of the pre-specified convergence criteria are satisfied, stop; otherwise continue.
9. Check the reduction in the number of complexes – if the minimum number of complexes required in the population, p_{min}, is less than p, remove the complex with the lowest ranked points; set $p = p–1$ and $S = p \times m$; return to step 6. If $p_{min} = p$, return to step 6.

3.3.1 Competitive Complex Evolution (CCE)

The CCE algorithms (Figure 3.2), based on Nelder and Mead (1965) simplex downhill search scheme, is presented below:

1. Initialize the number of points in a sub-complex (q), number of consecutive offspring generated by a sub-complex (α), number of evolution steps taken by each complex (β), where $2 \leq q \leq m$, $\alpha \geq 1$, and $\beta \geq 1$.
2. Assign weights- assign a triangular probability distribution to A^k; i.e.,

$$\rho_i = \frac{2(m+1-i)}{m(m+1)}, \ \mathrm{i} = 1,\ldots..,m. \tag{3.5}$$

The points x_1^k has the highest probability, $\rho_1 = 2/m+1$. The point x_m^k has the lowest probability, $\rho_m = 2/m(m+1)$.

3. Construct a sub-complex (Figure 3.3) by randomly selecting q points ($u_{1,}$…….u_q) from the complex (A^k) according to a triangular probability distribution. The probability distribution is specified such that the best point (i.e., the point with the best function value) has the highest chance of being chosen to form the sub-complex, and the worst point has the least chance. Store them in array $B = \{u_i,\ v_{i,}\ i = 1,\ldots\ldots,q\}$, where v_i is the function value associated with point u_i. Store in L, the location of A^k which are used to construct B.
4. Sort B and L so that q points are arranged in order increasing function value. Identify the worst point of the sub-complex and compute the centroid (g) of the sub-complex without including the worst point using the expression:

$$g = [1/(q-1)]\sum_{i=1}^{q-1} u_i \tag{3.6}$$

5. Attempt a reflection step (Figure 3.4) by reflecting the worst point through the centroid. If the newly generated point ($r = 2g - u_q$) is within the feasible space (Ω), compute the function value (f_r), and go to Step 6; otherwise, randomly generate a point (z) within the feasible space and compute f_z, set $r = z$ and $f_r = f_z$.
6. If the newly generated point is better than the worst point, i.e., $f_r < f_q$, replace the worst point (u_q) by the new point (r). Go to Step 9. Otherwise, go to Step 7.
7. Attempt a contraction (Figure 3.4) step by computing a point (c) halfway between the centroid (g) and the worst point (u_q), i.e., $c = (g + u_q)/2$ and function value f_c. If the contraction point is better than the worst point, i.e., $f_c < f_q$, replace the worst point (u_q) by the contraction point (c) and go to Step 9. Otherwise, go to Step 8.

8. Randomly generate a point (z) within the feasible space and compute f_z. Replace the worst point (u_q) by the randomly generated point (z).
9. Repeat Step 4 – Step 8 α times, where $\alpha \geq 1$ is the number of consecutive offspring generated by each sub-complex.
10. Repeat Step 1 – Step 9 β times, where $\beta \geq 1$ is the number of evolution steps taken by each complex.

3.3.2 Selection of the Parameters in the SCE Method

The number of complexes (p) and the number of points in each complex (m) are the two major parameters in SCE since they determine the total population size ($S = p \times m$). Generally, the larger the population size (S), the higher is the probability of locating global minima. The effectiveness of the algorithm depends on the larger value of S. However, as S increases, the evaluation of the objective function will increase and the efficiency of the algorithm will be affected. For small problem, $S = N + 1$ should be sufficient for finding optimal solution, while for complicated problem S will be larger.

The number of points in a complex (m) should not be too large. If the value m is too large, excessive computational time will be required. This results in reducing the computational efficiency. Duan et al. (1993) suggested that a good value for m is ($2N + 1$) or larger, where N is the number of parameter to be optimized.

The number of points in each sub-complex (q) may vary between two and m. However, a value of ($N + 1$) is suggested as a good choice, since ($N + 1$) points define a first order approximation of the function surface.

The number of consecutive offspring generated by each sub-complex, α, may be any number greater than or equal to one. If α is equal to one, it means that only one of the points will replaced before the sub-complex is placed back into the complex.

The number of sub-complexes chosen from each complex for reproduction, β, can take any number greater than one. If β is small, complexes will be shuffled frequently, and the search will fail to conduct independent exploration in the parameter space. On the other hand, if β is large, complex will move towards local minima. However, $\beta = m$ has been found to be a good choice.

3.3.3 Stopping Criteria of the SCE Algorithm

In SCE, there are four stopping criteria checked at each generation. If any of them is satisfied, computation is terminated immediately. The criteria are as follows:

1. Maximum number of function evaluation: if the search reaches maximum evaluation of the objective function without producing a point that has a criterion value less than a pre-defined limit, the algorithms will terminate. This criterion is very useful for cases when the model is time consuming and is required to stop in the middle of a loop.
2. Relative change of objective function: if the relative change of objective function values within the last k shuffling loops does not change more than a pre-specified percentage, the search will stop. This criterion implies the "convergence" may have been achieved or the computation got trapped in some local optima.
3. Best function value: if the best objective function value is less than a certain value, the 'optimal' is considered has been achieved.

4. Population convergence: if the population has converged into under pre-specified (e.g. 0.001) value of the original parameter space, the algorithms will terminate.

3.3.4 Exploration and Exploitation in SCE

Exploration and exploitation are the two techniques used by any efficient algorithm in the search for optimum solution. Exploration investigates new and unknown areas in the search space and exploitation uses the important information found at previously explored points (Muttil and Liong, 2002). SCE offers a reasonably good balance between exploration and exploration. SCE partitions total population of points into several communities. The partition of the population facilitates an extensive exploration of the solution space in different directions, thereby reducing the search getting trapped in local optima. It repeatedly evolves complexes based on Nelder and Mead simplex search technique in competitive complex evolution and thus directs the search in the feasible region. The population in the evolved complexes is mixed together to ensure information sharing. These multiple complex shuffling and complex evolution provide effective balance between exploration and exploitation.

3.3.5 Advantages of SCE Over Traditional Search Algorithms

SCE differs in many ways from traditional search algorithms. The most significant differences are:

1. SCE search uses a population of points in parallel, and thus not just a single point. The main advantage of this parallel search technique over traditional method, such as calculus and random search, is that it searches in all direction simultaneously. The chance of converging to a local optimum is greatly reduced.

2. SCE search is based on objective function value and does not depend on the derivative information. However, some traditional methods like gradient search algorithms require the construction or approximation of derivative information to search the feasible space. These methods fail to locate the global optimum when the response surface has discontinuities.
3. SCE follows probabilistic rules instead of deterministic rules for moving from one generation to the next. In the reproduction process, the parent solutions are selected to generate offspring using probabilistic transition rules. The individuals which have a lower objective function values have a greater chance of being selected for the procreation than those having high function values.
4. SCE search maintains a superior balance between exploration and exploitation.
5. SCE rounds the real decision value immediately to the nearest market sizes in the water distribution network design and removes the complexities occurred during rounding in the traditional methods (LP, NLP and DP). It always deals with discrete variables ensuring the quality of the solution.

3.4 PROPOSED SCHEME

In the present study, SCE (Duan et al., 1992) is coupled with EPANET to search the optimal decision variables (e.g., pipe diameters) for cases such as design of new or rehabilitation of existing networks. SCE generates possible combinations of trial solutions based on probabilistic and deterministic approaches and EPANET analyze the network using these proposed variable values. Later, SCE uses the feedback from EPANET to improve the quality of the solutions. To apply the model, SCE is modified to accommodate higher number decision variables.

3.4.1 Linking EPANET with SCE

In the proposed scheme, EPANET network solver (C code) is linked with SCE optimization algorithm (FORTRAN code). There is a function subprogram that is called by SCE main engine to evaluate the objective function values. A command statement in FORTRAN language calls EPANET network solver to determine the hydraulic performance of the network. Hence, the control variables (pipe diameter, roughness coefficients and nodal demands) are passed from the SCE optimizer to the network solver through a formatted input file (.INP) of EPANET. The simulation model solves the hydraulic equations and determines the values of the nodal pressure head, pipe flows etc. The nodal head resulted from simulation model is passed back to SCE optimizer. The strategy is depicted in Figure 3.5. The details of the working mechanism are discussed in Chapter 4.

3.4 CONCLUSIONS

Shuffled Complex Evolution (SCE) and the water distribution network simulation tool, EPANET, are discussed in details. SCE is well suited in this study since the algorithm itself learns to guide the search process towards a population with a higher quality of solution and provides efficient exploration and exploitation balance. The main advantages of SCE over the traditional search algorithms are also explained. The linking procedure between SCE and EPANET is described. The applications of the proposed model are demonstrated in the design of water distribution network and in the calibration of the model in Chapters 4 and 5, respectively.

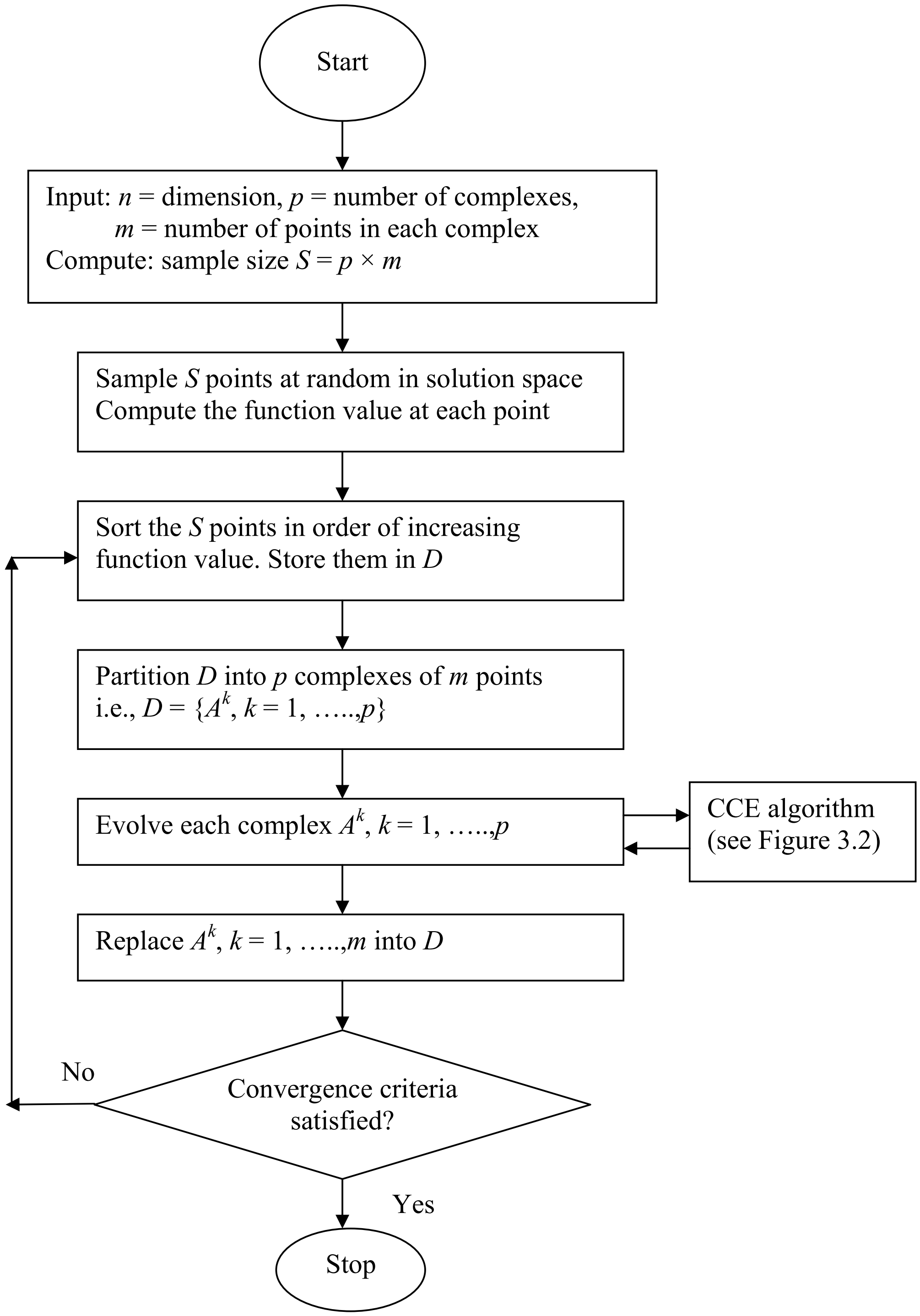

Figure 3.1 Flowchart of SCE Algorithm

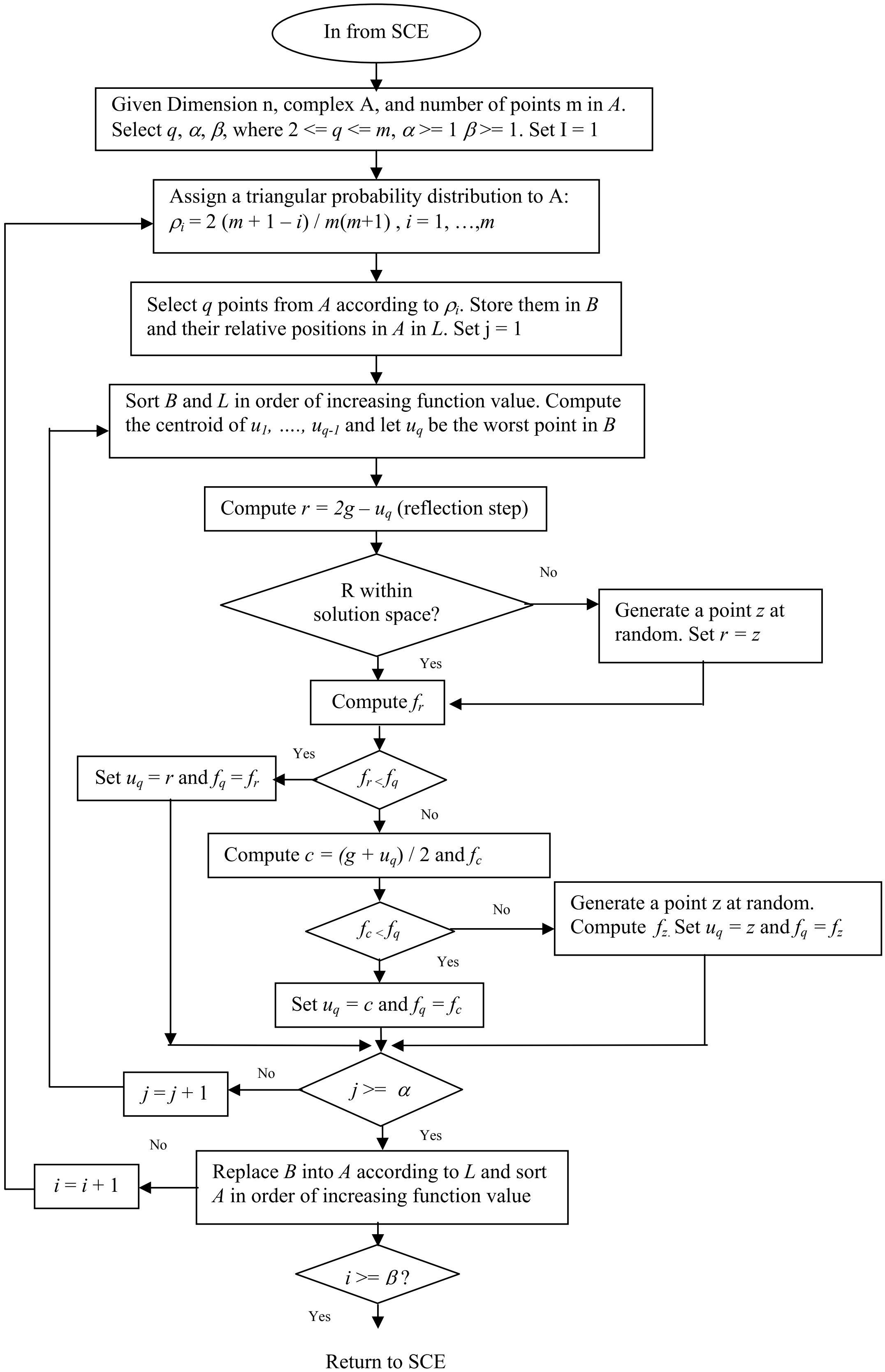

Figure 3.2 Flowchart of the CCE Strategy of SCE Algorithm

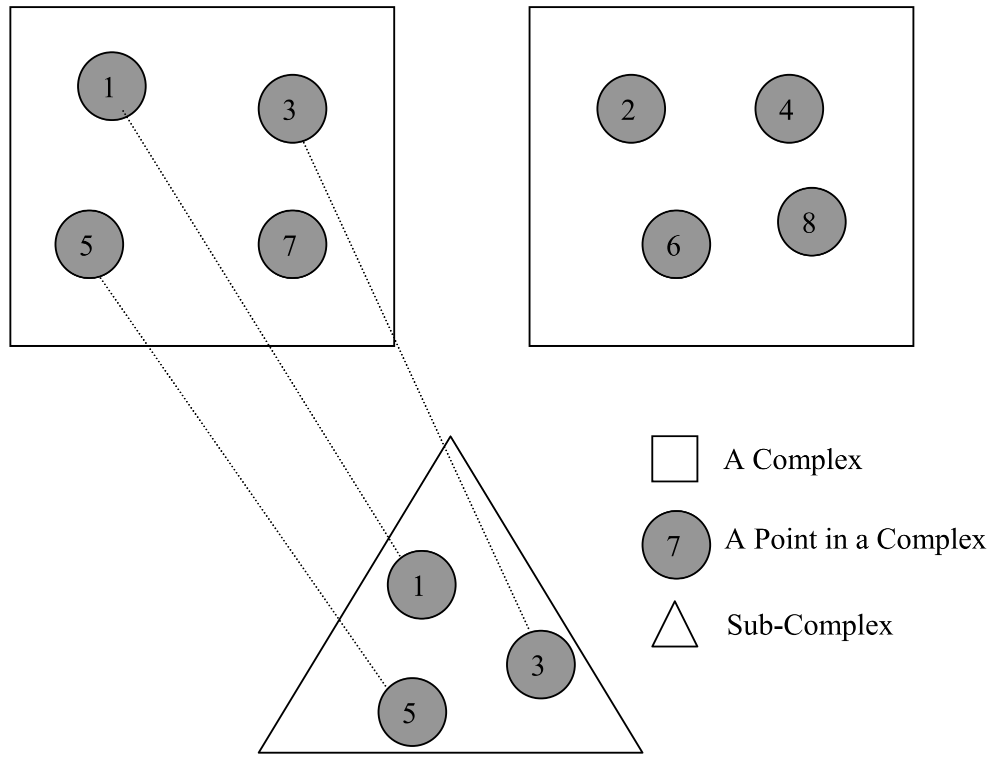

Figure 3.3 Shuffled Complex Evolution: Complexes and Sub-Complexes

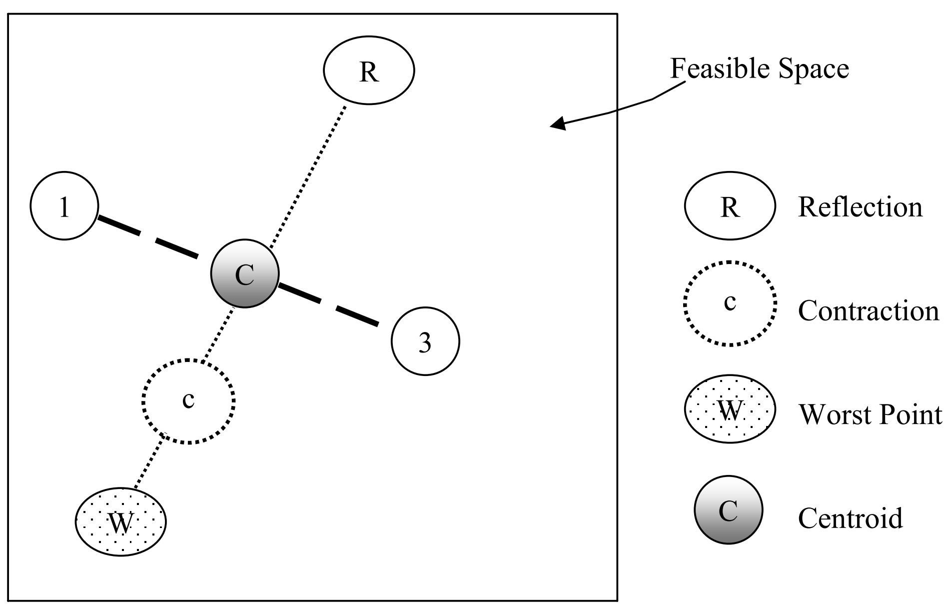

Figure 3.4 Solution Replacement Scheme in Simplex Method

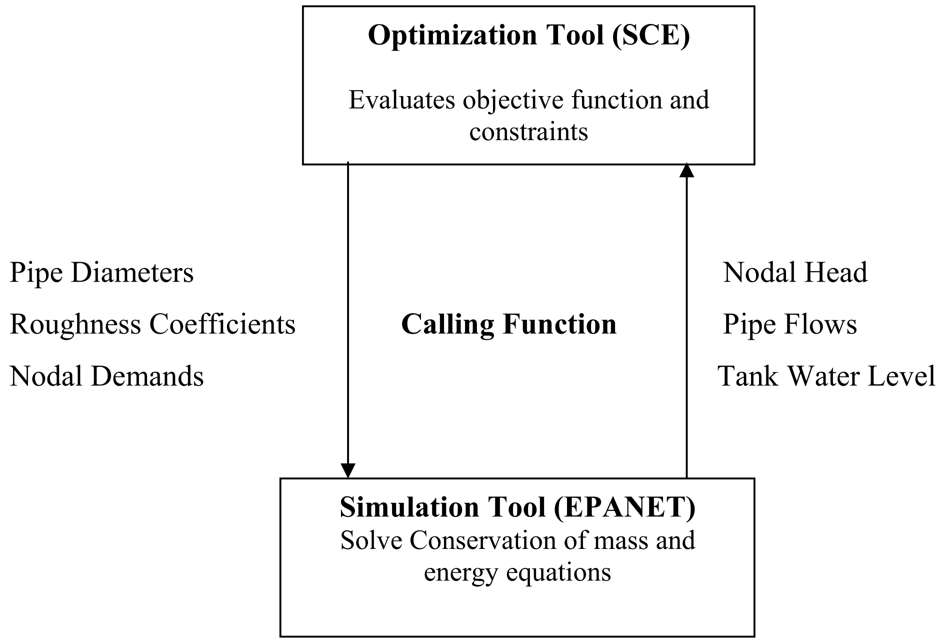

Figure 3.5 Linking Optimization and Simulation Models

CHAPTER 4

APPLICATIONS OF PROPOSED SCHEME TO DESIGN AND REHABILITATION OF WATER DISTRIBUTION NETWORKS

4.1 INTRODUCTION

The most common problems in water supply systems are designs of new water distribution networks or the expansion/modifications of existing ones. The main purpose is to satisfy the anticipated consumer demand at specified pressure heads, even during pipe failures. It is indeed a challenging task to ensure an economically feasible network system. If the network is designed with a set of undersized pipes, the minimum pressure head requirement may not be satisfied. On the other hand, if the network pipe is oversized, the design may not be economically feasible. Research focus has been to develop a suitable scheme able to determine the least cost for the water supply network which meets all hydraulic constraints. This chapter describes (1) the design and formulation of pipe network optimization problem followed by its applications (SCE-EPANET) on design of three new networks; and (2) the rehabilitation of an existing network.

4.2 DESIGN AND FORMULATION

The aim of design of water distribution network is to find the optimal pipe size for each pipe in a network for a given layout, demand loading conditions, and an operation policy. The model selects the optimal sizes in the final network satisfying all implicit and explicit constraints such as conservation of mass, conservation of energy, head constraints and design constraints. Implicit constraints involve the conservation of mass and conservation of energy whereas explicit constraints include the hydraulic constraints and diameter constraints. The hydraulic constraints deal with hydraulic head at the node which should be greater than a specified minimum value. If the hydraulic constraint is violated, a penalty function is introduced in the formulation. However, diameter constraints restrict the evolutionary algorithms to select the trial solution within a pre-defined limit. A hydraulic network solver handles the implicit constraints and evaluates the hydraulic performance of each trial solution that is a member of population of points. The hydraulic information obtained from network solver is used for the computation of fitness of the design. The fitness of a trial solution representing a pipe network design is based on the hydraulic performance obtained from the network solver. It consists of two parts. One is the network cost and the other is the penalty cost as discussed in the following sections.

4.2.1 Network Cost

The network cost is taken as the sum of the pipe costs expressed in terms of the cost per unit length. Individual cost for each pipe can be entered into or cost equation can be used to calculate the network cost. However, the design variables, namely pipe sizes are to be selected from a set of discrete commercially available diameters. Some models consider the diameters as a continuous variable. But this model does not guarantee the quality of the final solution because of the conversion to the nearest market sizes of the pipes. In this study, SCE's generated real values of the variables are immediately converted to the commercial diameters to calculate the network cost. The procedure is as follows:

- ❖ The commercial pipe sizes are sorted in ascending order.
- ❖ Costs for all available pipe sizes are given in the input file.
- ❖ Read the market sizes and cost from the table.

- Let $D(j)$ and $D(k)$ represent the SCE generated variables and market sizes of the pipes respectively.

  if $D(j) < D(k+1)$ and $D(j) \geq D(k)$ then

  if $D(j) \leq (D(k+1) + D(k))/2$ then

  $D(j) = D(k)$

  else

  $D(j) = D(k+1)$

  end if

  end if

The network cost depends on the market price of the pipes and is calculated by using the following equation:

$$C_N = \sum_{k=1}^{NP} c_k(D_k) \times L_k \tag{4.1}$$

where $c_k(D_k)$ = cost per unit length of the k^{th} pipe with diameter D_k; L_k = length of the k^{th} pipe; and NP = total number of pipes in the system.

4.2.2 Penalty Functions

The penalty term is triggered in the objective function whenever a solution does not meet the constraint(s) which are, for example, the minimum hydraulic head requirement(s). If any network design does not satisfy the minimum pressure requirement, an additional cost expressed as a penalty cost is added to the actual network cost. Different penalty methods have been proposed. The amount of penalty cost for any particular infeasible design network is computed on the basis of degree of pressure violation. The pressure violation (ΔH_j) at any node (j) is the difference between the minimum pressure head ($H_{min,j}$) and the simulated pressure head (H_j).

The maximum pressure deficit is often used in various studies to calculate the penalty cost (Simpson et al., 1994; Savic and Walters, 1997). Thus the equation can be expressed as,

$$C_P \text{ (penalty cost)} = p_c \times \max_j \Delta H_j = p_c \times \max_j [\max(H_{\min,j} - H_j, 0)] \qquad (4.2)$$

where p_c is the penalty factor.

In 1998, two different penalty equations were proposed by Abebe and Solomatine for two different conditions. If the pressure is less than zero, a high penalty cost is added to the actual cost of the network as follows

$$C_{p1} = 2 \times p_{c1} \times C_{max} - 2 \times C_N \qquad (4.3)$$

If the pressure is, however, less than minimum limit and greater than zero, the equation considered is,

$$C_{p2} = p_{c2} \times C_{max} \times \max_{j=1 \text{ to } NJ} (H_{\min,j} - H_j) \qquad (4.4)$$

where p_{c1} and p_{c2} are the penalty cost coefficients; C_{max} is the maximum possible cost calculated from the largest commercial pipe available; and ($H_{min,j}$- H_j) is the pressure deficit at node j.

Equations (4.2) and (4.4) consider only maximum pressure deficit and overlook the pressure deficits at other nodes. This means that in the case of equal maximum pressure violation, identical penalty cost is charged to both infeasible solutions. To incorporate pressure violations at other nodes, the summation of pressure deficits of all nodes is introduced in the penalty cost. Thus, the penalty cost function becomes:

$$C_P = p_c \times \sum_{j=1}^{NJ} \Delta H_j = p_c \times \sum_{j=1}^{NJ} (H_{\min,j} - H_j) \qquad (4.5)$$

where NJ = total number of junctions in the system where pressure violation occurs.

The penalty cost coefficient (p_c) in all penalty functions described above depends on the problem structure and has to be chosen carefully. The selection of appropriate penalty factor has been a problem because too small penalty factor drives the search in the infeasible region, whereas too big penalty factor enforces the search towards region of local optima and prevents strictly to use of the near optimal solution. In this study, the penalty factor is considered as a variable. The algorithm optimizes its value within a specified range limit. Since different points in the population have different degrees of feasibility, the individual point should have its own penalty coefficient. This approach auto-adapts the penalty factor and removes the difficulty of trial selection.

4.2.3 Constraints

In the design and optimization of water distribution network, the commonly considered constraints are summarized below:

1. Diameter constraints: pipe diameters should be selected from available commercial sizes. In this study, SCE generated sizes are converted to the nearest available market sizes immediately to satisfy these constraints.
2. Hydrodynamic constraints: these include conservation of mass and energy. Normally, EPANET network simulation model controls these constraints.
3. Pressure Constraints: The hydraulic pressure at each node of the network must be greater or equal to a pre-defined value. The pressure violation due to infeasible solution is accounted by penalizing extra charge on the network cost according to equation (4.5).

The formulation can mathematically be stated as follows:

$$\text{Minimize Cost } C = C_N + C_P \tag{4.6}$$

Subjected to:

$\sum Q_j = 0$ Conservation of mass equation (4.7a)

$\sum H_L = \sum P_E$ Conservation of energy equation (4.7b)

$H_j \geq H_{min,j}$ Nodal pressure constraints (4.7c)

$D_k \in \{D_1, D_2, D_3, D_4, \ldots\ldots\ldots, D_n\}$ (4.7d)

$D_{min} \leq D_k \leq D_{max}$ (4.7e)

$p_{cl} \leq p_c \leq p_{cu}$ (4.7f)

where Q_j = flow into or out of the node j; H_L = head loss in the pipe; P_E = applied pump energy; D_k = decision variables (pipe sizes); D_{min} = minimum market size; D_{max} = maximum market size; $\{D_1, D_2, D_3, D_4, \ldots\ldots\ldots, D_n\}$ = set of commercial available sizes; p_{cl} = lower bound of penalty factor; and p_{cu} = upper bound of penalty factor.

4.3 WORKING MECHANISM OF THE SCE-EPANET MODEL

A brief description of the steps of the SCE-EPANET for pipe network optimization is given below and illustrated in Figure 4.1:

1. Generation of population of points by SCE. Each point represents a combination of pipe diameters of the pipe network.
2. Computation of the network cost for each of the solutions after converting the randomly generated pipe sizes to the market sizes.
3. Read the network data from input file of the simulation tool.
4. Adjust the pipe diameter in the input file.
5. Perform hydraulic analysis of each network with EPANET network solver.
6. Read the nodal pressure from the output file of EPANET. Check the pressure at some nodes required to meet certain nodal pressures.
7. Compute penalty cost if the nodal head at any node is less than the required minimum.

8. Calculate the objective function which is the sum of the network cost and the penalty cost found in steps 2 and 7 respectively.
9. The total cost found in step 8 is used as a criterion value for each of the trial network.
10. Stopping criteria is checked, if any of the convergence criteria is satisfied, the process is terminated.

4.4 STOPPING CRITERIA USED IN DESIGN OF NETWORK

In the design of pipe network two stopping criteria are checked at each generation. If any of them is satisfied, it results in termination of the search algorithm. The criteria are as follows:

1. The relative change in the objective function within the last k shuffling loops has not changed more than a pre-specified percentage (1%).
2. The maximum number of function evaluation.

4.5 CASE STUDIES

4.5.1 Network 1 (Simple Network)

The first network, Figure 4.2, is a two-loop simple network presented by Alperovits and Shamir (1977) consisting of 8 pipes (each 1000 m long with Hazen-Williams C value of 130), 7 nodes and a single reservoir. The minimum pressure head requirement is 30 m for each node. Table 4.1 contains the commercially available pipe sizes and corresponding costs per unit length. There are 14 commercial diameters for consideration. SCE explores within the range of pipe diameters, minimum 1 in (25.4 mm) and maximum 24 in (609.6 mm). There are a total of $14^8 = 1.48\times10^9$ possible combinations. SCE, however, searches only a certain number possible combinations in the solution space to arrive at the optimal solution. The values of SCE parameters for this case study are: p = 4, p_{min} = 2, m = 20, q =10, α = 1, β = 20, total population = $p \times m$ = 80.Ten runs are performed using different initial seed values. Table 4.2 lists the optimal network solutions, total network cost, number of function evaluations, and the run time. The pressure at each node is shown in Table 4.3. Figure 4.3 depicts the reducing network cost with the increasing evaluation number.

Although the least cost ($419,000) resulting from SCE is the same as that obtained in works of other researchers (Savic and Walters, 1997; Abebe and Solomatine, 1998; Cunha and Sousa, 1999; and Eusuff and Lansey, 2003) SCE obtains this optimal solution significantly faster than their counterparts. SCE converges only after 758 evaluations with a total CPU time of 13 sec [Pentium 4 (Processor 1.79 GHz, RAM 512 MB)]. The average number of evaluations and computational time are 945 and 16 sec respectively. The other algorithms like GA (65,000 evaluations), Simulated Annealing (25,000 evaluations), GLOBE (1,373 evaluations), SFLA (11,323 evaluations) converged very slowly.

4.5.2 Network 2 (Hanoi Network)

The second water distribution network considered in this study is the network in Hanoi, Vietnam. The network (Fujiware and Khang, 1990), Figure 4.4, consists of one reservoir (node 1), 31 demand nodes and 34 pipes (roughness coefficients of 130 for all pipes). Data used in this network are shown in Table 4.4. The minimum pressure head requirement at each node is 30 m. The cost of commercially available pipe sizes

(12, 16, 20, 24, 30, 40; in inches) was calculated using the following equation (Fujiwara and Khang, 1990):

$$C_k = 1.1 \times D_k^{1.5} \tag{4.8}$$

where C_k is the cost per unit length of the k^{th} pipe.

The values of the SCE parameters used to solve this problem are: p =10, p_{min} = 10, m =30, q =15, α = 1, β =30 and the total population = $p \times m$ = 300. Ten runs are performed with different initial seed values. The results are shown in Table 4.5. Table 4.5 shows the solutions obtained by other researchers (Savic and Walters, 1997; Abebe and Solomatine, 1998; Cunha and Sousa, 1999; and Eusuff and Lansey, 2003) as well.

The final network cost ($6.22 million) obtained by SCE requires 34,373 function evaluations and a CPU time of only 15 minutes. Although Savic and Walters (1997) and Eusuff and Lansey (2003) obtained a slightly smaller network cost ($6.073 million), the resulting pressure heads at nodes 13 and 30 do not meet the head constraints (Table 4.6); also their CPU times are relatively very high (3 hr). Abebe and Solomatine (1998) used GA and ACCOL to solve the problem; their solutions are certainly not optimal compared to those of other researchers. The solution by Cunha and Sousa (1999) is definitely most optimal ($6.056 million) among the results shown in Table 4.5. The drawbacks, however, are: (1) the pressure head requirements at nodes 13, 16, 17, 27, 29 and 30 are not met (Eusuff and Lansey, 2003); and (2) they require a much higher number of function evaluations and, hence, longer CPU time.

4.5.3 Network 3 (Real Irrigation Network at Ecuador)

The schematic diagram of a real irrigation network at Ecuador is shown in Figure 4.5. This network consists of 814 pipes and 812 nodes and one reservoir (source node). The network configuration is shown in Appendix A.2. The length of the pipe ranges from 0.72 m to 9,778 m with Darcy-Weisbach roughness coefficients of 0.05 mm for all pipes. The minimum pressure head requirement is 1.7 m for each node. Twenty four discrete pipe diameters are commercially available from which decision variables are to be chosen. The market sizes and corresponding prices are presented in Table 4.7. The cost per unit length of the pipe can also be calculated by the following equation:

$$C_k = 0.000229839 \times D_k^2 + 0.166464453 \times D_k - 5.770407444 \qquad (4.9)$$

where C_k is the cost per meter and D_k is the diameter in millimeters of the k^{th} pipe.

4.5.3.1 Usual Approach

The network is designed by considering each pipe as a variable. This results in a 814 dimensional problem. The diameter of each pipe is to be selected from 24 available pipe sizes. This yields a total of 24^{814} possible design alternatives which are simply prohibitive for consideration. However, SCE is able to search the optimum from this high dimensional solution space. The SCE parameters used for this problem are: p = 30, p_{min} = 30, m = 100, q = 60, α = 1, β = 30, total population= $p \times m$ = 3,000. Five runs are performed using the same random seed number. Initially, all pipes are assigned to one random size. After the end of first run, the best point is then used as an initial point in the next run. This process continues up to five runs. SCE yields the optimal design satisfying the minimum pressure requirement at each node. The minimum cost of 101.4 million dollar is achieved in only 8 days and 15 hours with 7,469,630 function evaluations.

Since the number of dimensions is very high, a new strategy is incorporated to improve the capability of SCE to handle higher dimensional problem. Instead of introducing only the best point from the first run for the following run, several points from the first run are considered as well. The selected points are:

1) The best point from each generation: From each generation, only the solution with the minimum cost solution (best fitted point) will be used in the next run. Thus, if SCE is run with two hundred generations, 200 best fit points each from a generation are forwarded to the next run.
2) Some best points from the last generation: When the program ends, some population of points from the very last generation are introduced in the next run.

The points found in (1) and (2) contribute around fifty percent of the initial population in the subsequent run. The rest of the points are generated randomly. This process improves the robustness of SCE. After several runs significant improvement of cost (96.5 million) is achieved satisfying all hydraulic constraints. However, due to the presence of numerous local optima in the solution space, the global minima may not be guaranteed. Since some percentage of good points is being introduced, the search is forced in the prescribed direction and the algorithm converges earlier because of loosing diversity. This situation is tackled by increasing the total number of population as well as decreasing the lower limit of the penalty coefficients. The lower limit of penalty coefficients are reduced to allow some more points which have failed to meet the feasibility criteria. If these suboptimal points are permitted to include their characteristics, the chance of getting global minima is increased significantly. The final result shows that SCE reaches the minimum cost solution of 94.4 million with total 16,763,746 function evaluations.

4.5.3.2 Clustering Approach

The usual approach involves manual inclusion of some best points from each generation as well as from the last generation in the subsequent run to include advance knowledge on the solution characteristics. However, the points selected manually are based on their objective function values which may not lead the search to global optima. This process does not ensure the solutions from different regions of the search space. In order to include good representative points from different regions and to keep diversity, Kohonen Neural Network (KNN) is applied in this study. KNN described in Chapter 2 partitions a number of points into different clusters (groups). The points in each cluster contain similar characteristics. Each cluster has a center which is called winning neuron acts as the representative of the group. To solve high dimensional network problem (say N variables), all cluster centers from various groups may be the initial input points in the successive run of SCE. The procedure is briefly described below:

a) Run SCE, of N variables, with all initial points in the population generated randomly;
b) Take S points from the SCE at the end of the first run;
c) Calculate the standard deviation of each variable from different solutions;
d) Select only M number of variables from N when N is very large. The selection of M variables is based on their standard deviations; the one with large

standard deviations should be considered. Small standard deviation implies that the variable is not sensitive. The ($N - M$) number of variables are left out;

e) Create a file of S points with only M variables now;

f) Apply KNN to partition S points into R clusters;

g) Identify cluster centers;

h) Create an input data file with R points and, at the same time, insert back the remaining (N-M) variables which were excluded in step (d). The values used for these (N-M) variables are their mean, minimum and maximum values. As a result, a total of 3R points are generated.

i) Use these 3R points in the SCE to continue the next run.

In the present study with irrigation network, SCE runs with 3,000 points. After the end of the first run, 3,000 points are divided into 200 (= R) clusters using KNN. Later on, total 600 (3 × R) points from KNN together with the best points from each generation of the previous run are included in the second run of SCE. Similar procedure follows for the subsequent runs. The final solution yields a total cost of 92.66 million with a total number of evaluations of 26,729,764 meeting all prescribed constraints. The results are given in Table 4.8. The pressure heads at each junction are shown in Appendix A.3. It should be noted that the pressure head at each node is greater than the minimum requirement of 1.7 m. The advantage of using KNN in this study is that it overcomes the difficulty of manual inclusion of best individuals and expedites the SCE computation in reaching the optimal solution; often it requires only two or three runs.

4.6 REHABILITATION OF AN EXISTING NETWORK

Many existing water networks may become inadequate with their water supply as the population growth exceeds certain threshold value. The inadequacy could be in the form of the water consumption volume or pressure heads. In addition, because of the tuberculation of the pipes, leakage, breakage, and corrosion, head losses, operation and maintenance cost are increased significantly over time. For this reason, the network should be updated by paralleling or replacing or cleaning the existing pipes at regular interval of times.

The rehabilitation task of existing water distribution network is to select a set of combination of pipes, pipe rehabilitation actions, pump capacities, tank sizes, valve sizes and setting for a given layout and demand patterns (Wu and Simpson, 2001). The main target is to establish an effective network to supply water with adequate nodal pressure. Hence, new pipes are designed to expand an existing network in the newly developed area or replace an existing one due to damage or leakage or to set parallel to meet the increased demand.

The New York City water tunnel is a rehabilitation problem considered in this study. The network shown in Figure 4.6 has been solved by Dandy et al. (1996), Eusuff and Lansey (2003), Maier et al. (2003). It comprises of 21 pipes and 20 nodes. Water is fed from a single reservoir providing a head of 300 m. The details of the network configuration (layout, pipe length, node elevation etc) are described in Table 4.9. The goal is to determine the pipe sizes which have to be placed in parallel of the existing pipes to meet the increased nodal demand at certain nodes. The demands at nodes 16,17,18,19 and 20 are increased due to community development in the area of

RICHMOND and QUEENS. Consequently, the existing network system is not adequate to meet the increase in nodal demands; this is partially also, due to the aging of the pipes. The available market sizes of the pipes and the corresponding pipe costs are shown in Table 4.10. There are fifteen available commercial pipe diameters and sixteen different decision options including "do nothing" option. Since the optimization model can assign any of these decisions to each of the 21 pipes; the search space consists of a total of 16^{21} (1.93×10^{25}) possible combinations of solutions.

Table 4.11 shows that the solutions obtained by different researchers differ significantly. For example, Dandy et al. (1996) found that pipes 15,16,17,18,19 and 21 are to be duplicated by new pipes in parallel, whereas Maier et al. (2003) and Eusuff and Lansey (2003) identified pipes 7, 16, 17,18,19 and 21. In addition, the cost ($38.80 mill.) and the corresponding average number of function evaluations (96,750) by Dandy et al. (1996) are higher than those of their counterparts. Lippai et al. (1999) and Eusuff and Lansey (2003) obtained the same solution. However, their solutions are infeasible because the minimum pressure requirement at node 19 (Table 4.12) is not fully satisfied although the deficit is very small, 0.02 (Maier et al., 2003). Maier et al. (2003) used ACOAs and obtained the optimal solution cost of 38.64 million dollar with the average function evaluations of 13,928 which is 85.6 % lower than that of Dandy et al. (1996).

In this study, SCE with EPANET simulation model is able to reach the same optimal solution (Table 4.11) of Maier et al. (2003) satisfying at the same time all pressure requirements (Table 4.12). However, SCE requires only 7,650 function evaluations which is 45 % and 92 % lower than that of Maier et al. (2003) and Dandy et al. (1996)

respectively. Figure 4.7 depicts the reducing network cost with the increasing number of evaluations. It should be noted that the total CPU time of this study is 1 min 50 sec in the same PC.

4.7 CONCLUSION

A scheme based on coupled SCE and EPANET is created. Suggestions as to how to make the scheme more robust and efficient are given. A robust and efficient scheme is essential in the design of water distribution networks and rehabilitation of existing networks. It is found that the proposed scheme is capable to solve both small as well as large water distribution networks. It searches with initially random diameter sizes assigned to all pipes in the network and eventually yields minimum cost with optimal pipe sizes satisfying all prescribed hydraulic constrains. The application of KNN, to suggest good starting solutions for the subsequent runs, also enhances the robustness of the model. In all case studies considered the model reaches optimal solution without any prior knowledge of the suitable combinations of pipe diameters. The optimal solution obtained is accompanied with relatively (much) smaller number of evaluations compared to algorithms used by other researchers.

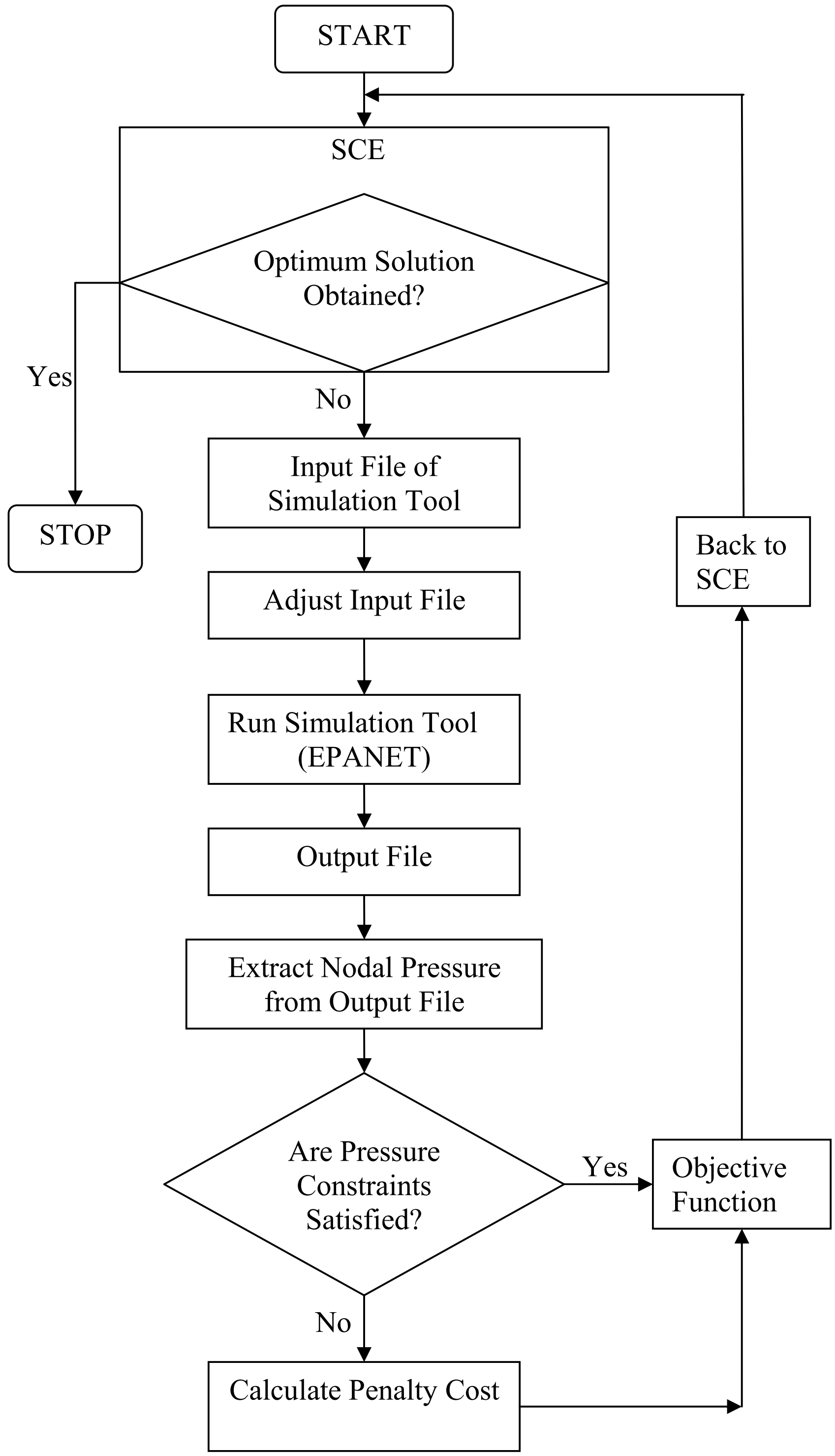

Figure 4.1 Flow Chart of Design Problem

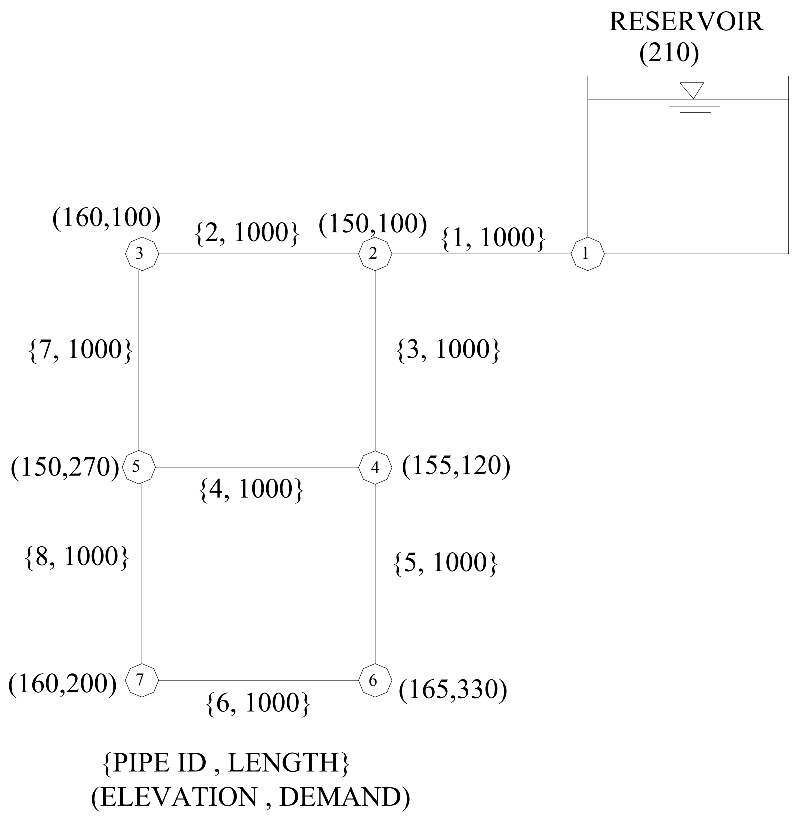

Figure 4.2 Two-Loop Network (Network 1)

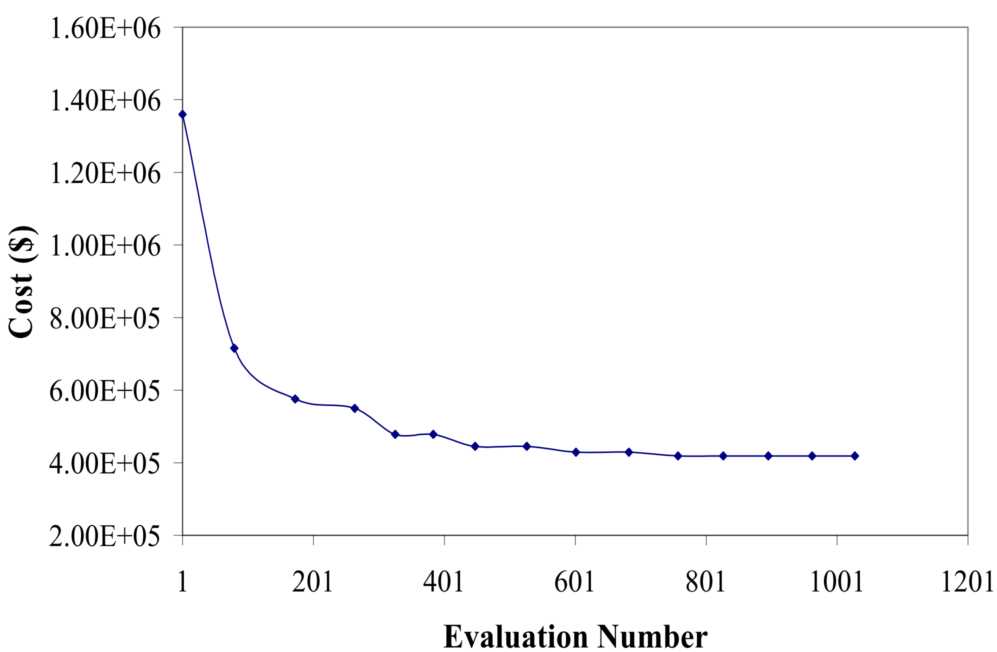

Figure 4.3 Cost Evolution (Network 1): SCE Algorithm

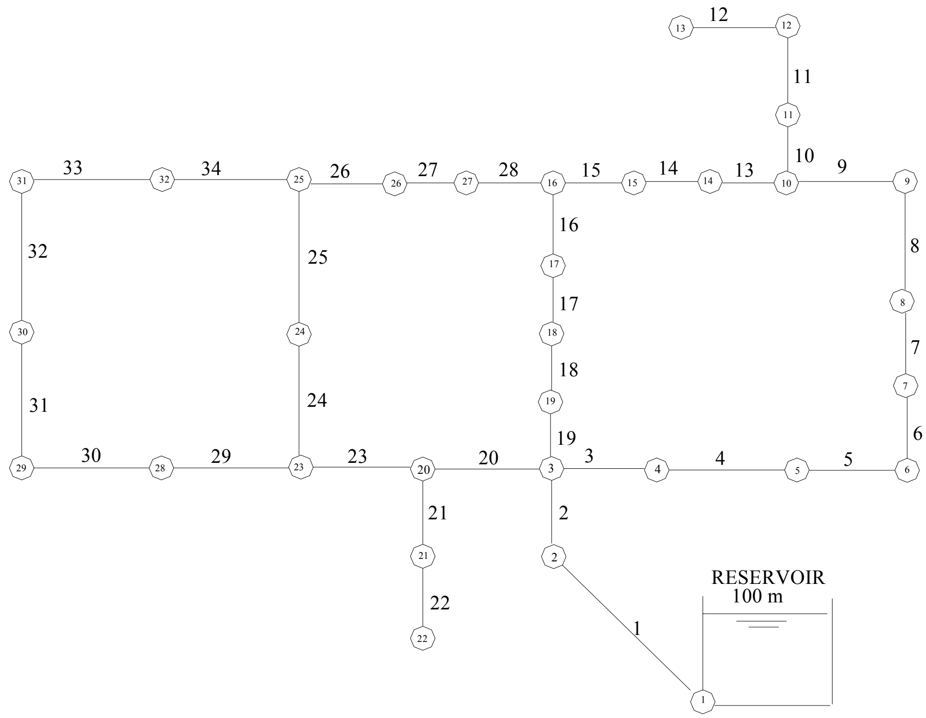

Figure 4.4 Hanoi Network (Network 2)

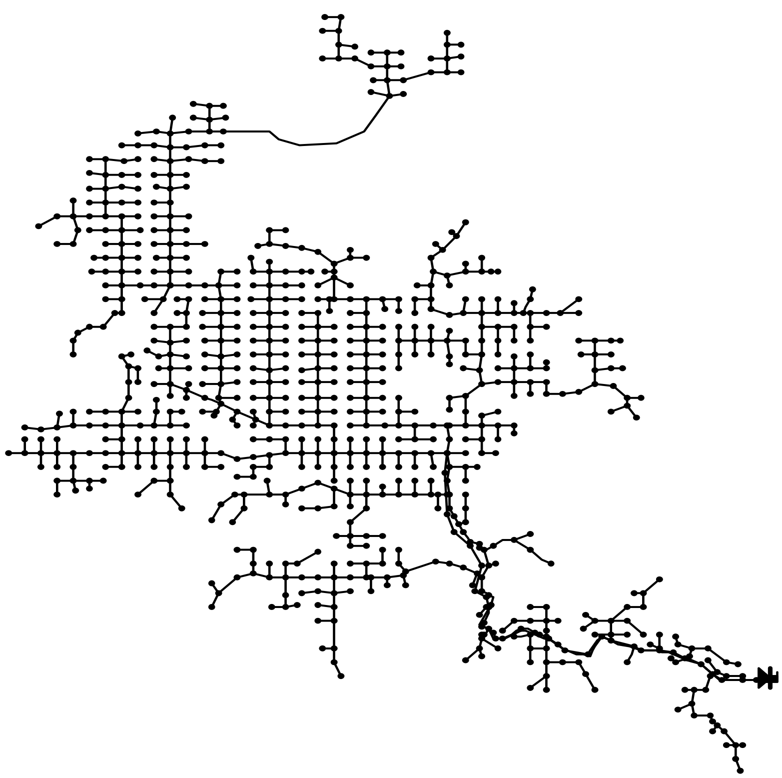

Figure 4.5 Large Irrigation Network (Network 3)

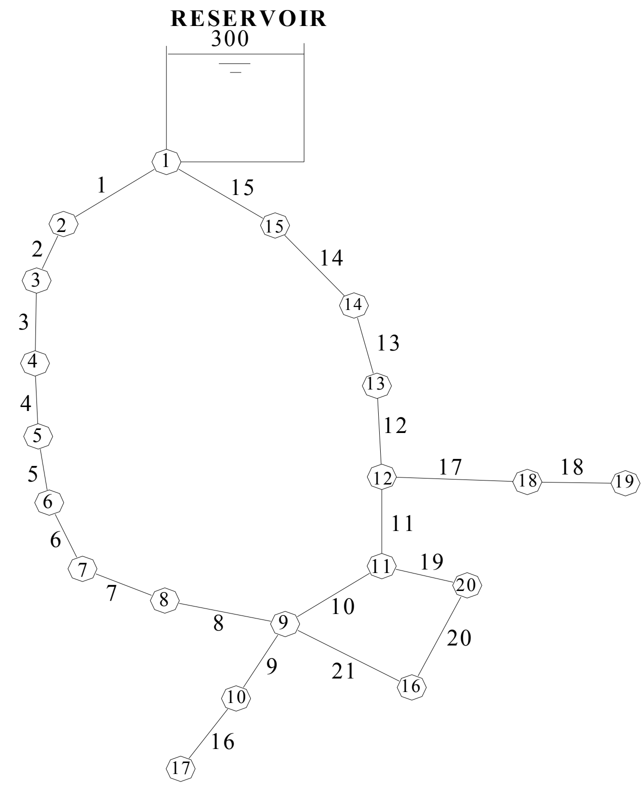

Figure 4.6 New York City Water Tunnel (Rehabilitation)

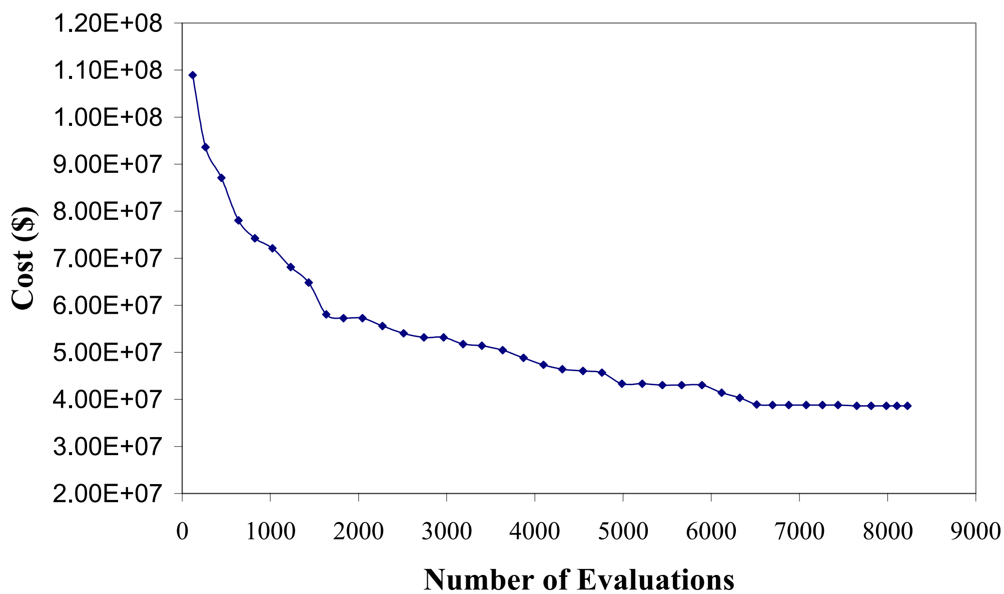

Figure 4.7 Evolution of Cost with SCE Algorithm (Rehabilitation)

Table 4.1 Costs of Pipes of Different Diameters (Network 1)

Diameter (in)	Diameter (mm)	Cost (Units)
1	25.4	2
2	50.8	5
3	76.2	8
4	101.6	11
6	152.4	16
8	203.2	23
10	254.0	32
12	304.8	50
14	355.6	60
16	406.4	90
18	457.2	130
20	508.0	170
22	558.8	300
24	609.6	550

Table 4.2 Results of Two-Loop Network (Network 1)

Pipe No.	Pipe Diameter (in)					
	Savic and Walters (1997)		Abebe and Solomatine (1998)	Cunha and Sousa (1999)	Eusuff and Lansey (2003)	Shuffled Complex Evolution
	GA1	GA2	GLOBE	SA	SFLA	SCE
1	18	20	18	18	18	18
2	10	10	10	10	10	10
3	16	16	16	16	16	16
4	4	1	4	4	4	4
5	16	14	16	16	16	16
6	10	10	10	10	10	10
7	10	10	10	10	10	10
8	1	1	1	1	1	1
Cost ($)	419,000	420,000	419,000	419,000	419,000	419,000
FEN[1]	65,000	65,000	1,373	25,000	11,323	758
Run Time	10 min	10 min	7 min	40 sec	-	13 sec

[1]Function Evaluation Number

Table 4.3 Pressures at Various Nodes (Network 1)

Node	Pressure Head (m)
2	53.25
3	30.46
4	43.45
5	33.81
6	30.44
7	30.55

Table 4.4 Data of Hanoi Network (Network 2)

Node Data		Pipe Data	
Node	Demand (m^3/h)	Pipe	Length (m)
1	-19,940	1	100
2	890	2	1,350
3	850	3	900
4	130	4	1,150
5	725	5	1,450
6	1,005	6	450
7	1,350	7	850
8	550	8	850
9	525	9	800
10	525	10	950
11	500	11	1,200
12	560	12	3,500
13	940	13	800
14	615	14	500
15	280	15	550
16	310	16	2,730
17	865	17	1,750
18	1,345	18	800
19	60	19	400
20	1,275	20	2,200
21	930	21	1,500
22	485	22	500
23	1,045	23	2,650
24	820	24	1,230
25	170	25	1,300
26	900	26	850
27	370	27	300
28	290	28	750
29	360	29	1,500
30	360	30	2,000
31	105	31	1,600
32	805	32	150
		33	860
		34	950

Table 4.5 Optimal Solutions Resulting from Various Search Techniques: Hanoi Network (Network 2)

Pipe Number	Pipe Diameter (in)					
	Savic and Walters (1997) & Eusuff and Lansey (2003)		Abebe and Solomatine (1998)		Cunha and Sousa (1999)	Shuffled Complex Evolution
	GA1 & SFLA	GA2 & SFLA	GA	ACCOL	SA	SCE
1	40	40	40	40	40	40
2	40	40	40	40	40	40
3	40	40	40	40	40	40
4	40	40	40	40	40	40
5	40	40	30	40	40	40
6	40	40	40	30	40	40
7	40	40	40	40	40	40
8	40	40	30	40	40	30
9	40	30	30	24	40	30
10	30	30	30	40	30	30
11	24	30	30	30	24	30
12	24	24	30	40	24	24
13	20	16	16	16	20	16
14	16	16	24	16	16	12
15	12	12	30	30	12	12
16	12	16	30	12	12	24
17	16	20	30	20	16	30
18	20	24	40	24	20	30
19	20	24	40	30	20	30
20	40	40	40	40	40	40
21	20	20	20	30	20	20
22	12	12	20	30	12	12
23	40	40	30	40	40	30
24	30	30	16	40	30	30
25	30	30	20	40	30	24
26	20	20	12	24	20	12
27	12	12	24	30	12	20
28	12	12	20	12	12	24
29	16	16	24	16	16	16
30	16	16	30	40	12	16
31	12	12	30	16	12	12
32	12	12	30	20	16	16
33	16	16	30	30	16	20
34	20	20	12	24	24	24
Cost ($ mill)	6.073	6.195	7.0	7.8	6.056	6.22
FEN[1]	-	-	16,910	3,055	53,000	34,373
Run Time	3 hr	3 hr	1 hr15min	15 min	2 hr	15 min

[1]Function Evaluation Number

Table 4.6 Pressure Heads Resulting from Various Search Techniques: Hanoi Network (Network 2)

Node Number	Nodal Pressure (m)					
	Slavic and Walters (1997) & Eusuff and Lansey (2003)		Abebe and Solomatine (1998)		Cunha and Sousa (1999)	Shuffled Complex Evolution
	GA1 & SFLA	GA2 & SFLA	GA	ACCOL	SA	SCE
1	100	100	100	100	100	100
2	97.14	97.14	97.14	97.14	97.14	97.14
3	61.63	61.63	61.67	61.67	61.63	61.67
4	56.83	57.26	58.59	57.68	56.82	57.54
5	50.89	51.86	54.82	52.75	50.86	52.43
6	44.62	46.21	39.45	47.65	44.57	47.13
7	43.14	44.91	38.65	42.95	43.10	45.92
8	41.38	43.40	37.87	41.68	41.33	44.55
9	39.97	42.23	35.65	40.70	39.91	40.27
10	38.93	38.79	34.28	32.46	38.86	37.24
11	37.37	37.23	32.72	32.08	37.30	35.68
12	33.94	36.07	31.56	30.92	33.87	34.52
13	29.72*	31.86	30.13	30.56	29.66*	30.32
14	35.06	33.19	36.36	30.55	34.94	34.08
15	33.07	32.90	37.17	30.69	32.88	34.08
16	30.15	33.01	37.63	30.74	29.79*	36.13
17	30.24	40.73	48.11	46.16	29.95*	48.64
18	43.91	51.13	58.62	54.41	43.81	54.00
19	55.53	58.03	60.64	60.58	55.49	59.07
20	50.39	50.63	53.87	49.23	50.43	53.62
21	41.03	41.28	44.48	47.92	41.07	44.27
22	35.86	36.11	44.05	47.86	35.90	39.11
23	44.15	44.61	39.83	41.96	44.24	38.79
24	38.84	39.54	30.51	40.18	38.50	36.37
25	35.48	36.40	30.50	38.95	34.79	33.16
26	31.46	32.93	32.14	36.01	30.87	33.44
27	30.03	32.18	32.62	35.93	29.59*	34.38
28	35.43	36.02	33.52	36.47	38.60	32.64
29	30.67	31.38	31.46	36.45	29.64*	30.05
30	29.65*	30.47	30.44	36.54	29.90*	30.10
31	30.12	30.95	30.39	36.64	30.18	30.35
32	31.36	32.24	30.17	36.76	32.64	31.09

*Infeassible solution (pressure less than 30) when EPANET network solver was used.

Table 4.7 Market Pipe Sizes and Pipe Costs: Irrigation Network (Network 3)

Serial No.	Diameter (mm)	Cost ($/m)
1	150	24.4
2	200	36.7
3	250	50.2
4	300	64.9
5	350	80.6
6	400	97.6
7	450	115.7
8	500	134.9
9	600	176.9
10	700	223.4
11	800	274.5
12	900	330.2
13	1000	390.5
14	1100	455.4
15	1200	525.0
16	1300	599.1
17	1400	677.8
18	1500	761.1
19	1600	849.0
20	1800	1038.5
21	1900	1140.2
22	2000	1246.5
23	2200	1472.9
24	2400	1717.6

Table 4.8 Optimal Pipe Sizes for Irrigation Network (Network 3)

Pipe No	Diameter (mm)	Pipe No	Diameter (mm)	Pipe No	Diameter (mm)	Pipe No	Diameter (mm)
1	1800	62	350	123	250	184	250
2	1900	63	300	124	300	185	600
3	1900	64	250	125	250	186	900
4	1800	65	800	126	300	187	250
5	1900	66	450	127	300	188	350
6	1900	67	350	128	1000	189	350
7	1800	68	350	129	250	190	1800
8	350	69	200	130	500	191	2200
9	250	70	350	131	450	192	250
10	1900	71	300	132	250	193	1900
11	250	72	350	133	300	194	300
12	2000	73	300	134	350	195	250
13	300	74	350	135	300	196	900
14	900	75	250	136	1800	197	300
15	1900	76	700	137	900	198	300
16	250	77	250	138	300	199	500
17	1900	78	300	139	400	200	300
18	300	79	800	140	350	201	250
19	300	80	350	141	800	202	350
20	500	81	300	142	300	203	400
21	250	82	350	143	350	204	350
22	250	83	250	144	250	205	300
23	400	84	450	145	450	206	800
24	350	85	700	146	350	207	350
25	250	86	200	147	300	208	300
26	2000	87	500	148	350	209	250
27	1800	88	200	149	300	210	250
28	300	89	300	150	250	211	1400
29	250	90	1000	151	250	212	200
30	300	91	2000	152	350	213	700
31	350	92	350	153	400	214	450
32	1900	93	1900	154	300	215	300
33	300	94	900	155	350	216	1000
34	350	95	250	156	300	217	250
35	250	96	800	157	500	218	300
36	300	97	400	158	500	219	900
37	350	98	400	159	900	220	450
38	350	99	300	160	250	221	250
39	250	100	900	161	200	222	300
40	350	101	250	162	300	223	700
41	250	102	900	163	1100	224	300
42	500	103	300	164	450	225	300
43	300	104	350	165	450	226	150
44	400	105	350	166	300	227	250
45	400	106	350	167	250	228	400
46	200	107	800	168	400	229	350
47	250	108	300	169	350	230	200
48	250	109	450	170	200	231	800
49	300	110	700	171	300	232	250
50	300	111	350	172	800	233	150
51	1800	112	700	173	400	234	200
52	350	113	300	174	1000	235	900
53	2000	114	600	175	400	236	350
54	2000	115	800	176	300	237	300
55	1900	116	450	177	250	238	250
56	2400	117	250	178	450	239	250
57	250	118	500	179	2400	240	300
58	350	119	300	180	350	241	150
59	300	120	1900	181	250	242	600
60	200	121	200	182	300	243	300
61	1900	122	350	183	400	244	400

Table 4.8 (cont'd)

Pipe No	Diameter (mm)	Pipe No	Diameter (mm)	Pipe No	Diameter (mm)	Pipe No	Diameter (mm)
245	350	309	1300	373	200	437	400
246	200	310	300	374	250	438	300
247	350	311	350	375	250	439	300
248	400	312	1100	376	1000	440	250
249	300	313	300	377	1500	441	700
250	350	314	200	378	800	442	450
251	900	315	1200	379	450	443	300
252	700	316	300	380	350	444	250
253	250	317	200	381	1000	445	200
254	1200	318	400	382	250	446	250
255	1200	319	300	383	300	447	1500
256	1300	320	300	384	500	448	200
257	2200	321	300	385	300	449	1400
258	250	322	250	386	250	450	1600
259	900	323	1100	387	250	451	300
260	300	324	250	388	300	452	300
261	200	325	250	389	250	453	400
262	200	326	1100	390	1900	454	600
263	2200	327	250	391	350	455	300
264	1000	328	200	392	300	456	900
265	900	329	1100	393	1500	457	200
266	350	330	900	394	350	458	600
267	250	331	250	395	200	459	450
268	200	332	700	396	300	460	350
269	2000	333	400	397	300	461	700
270	900	334	300	398	300	462	300
271	300	335	700	399	250	463	1400
272	250	336	350	400	500	464	300
273	900	337	700	401	250	465	250
274	200	338	450	402	450	466	200
275	300	339	250	403	250	467	250
276	800	340	400	404	250	468	350
277	250	341	350	405	450	469	400
278	350	342	250	406	300	470	350
279	900	343	250	407	200	471	700
280	250	344	250	408	450	472	400
281	250	345	600	409	200	473	300
282	900	346	250	410	300	474	300
283	250	347	300	411	300	475	200
284	250	348	250	412	300	476	300
285	800	349	300	413	200	477	1500
286	250	350	400	414	250	478	1500
287	350	351	350	415	200	479	450
288	900	352	350	416	800	480	350
289	300	353	300	417	250	481	1500
290	800	354	350	418	300	482	1400
291	800	355	300	419	400	483	200
292	300	356	700	420	350	484	350
293	600	357	300	421	1300	485	1100
294	250	358	400	422	300	486	250
295	600	359	1800	423	300	487	250
296	250	360	450	424	200	488	500
297	2200	361	250	425	1500	489	1600
298	250	362	350	426	300	490	500
299	300	363	400	427	700	491	250
300	2000	364	300	428	300	492	600
301	1900	365	700	429	250	493	250
302	300	366	300	430	300	494	350
303	900	367	250	431	1900	495	800
304	300	368	200	432	200	496	300
305	350	369	700	433	1900	497	300
306	1300	370	250	434	1800	498	700
307	250	371	400	435	250	499	250
308	250	372	700	436	1800	500	250

Table 4.8 (cont'd)

Pipe No	Diameter (mm)	Pipe No	Diameter (mm)	Pipe No	Diameter (mm)	Pipe No	Diameter (mm)
501	800	565	350	629	200	693	400
502	150	566	450	630	800	694	1000
503	400	567	250	631	250	695	450
504	250	568	300	632	300	696	400
505	300	569	250	633	400	697	400
506	300	570	200	634	300	698	450
507	300	571	900	635	350	699	300
508	1100	572	1600	636	250	700	1600
509	300	573	350	637	300	701	1800
510	300	574	350	638	350	702	1800
511	1100	575	900	639	250	703	1500
512	250	576	2000	640	450	704	400
513	350	577	300	641	300	705	800
514	1100	578	250	642	450	706	1900
515	250	579	300	643	800	707	250
516	1100	580	300	644	300	708	1100
517	250	581	350	645	250	709	300
518	300	582	450	646	450	710	300
519	600	583	500	647	400	711	300
520	250	584	350	648	350	712	500
521	200	585	700	649	1100	713	350
522	500	586	1500	650	350	714	1800
523	200	587	250	651	250	715	250
524	250	588	300	652	350	716	1000
525	600	589	200	653	2000	717	900
526	300	590	1300	654	400	718	800
527	400	591	250	655	300	719	250
528	450	592	1000	656	250	720	300
529	300	593	250	657	250	721	300
530	250	594	300	658	2200	722	300
531	400	595	300	659	700	723	250
532	350	596	350	660	400	724	300
533	400	597	900	661	350	725	400
534	350	598	1000	662	300	726	300
535	250	599	1300	663	250	727	300
536	1800	600	300	664	1000	728	300
537	1100	601	250	665	300	729	300
538	1800	602	1400	666	200	730	250
539	1000	603	350	667	250	731	250
540	500	604	350	668	1500	732	300
541	400	605	200	669	1800	733	250
542	200	606	2000	670	200	734	700
543	250	607	300	671	500	735	800
544	250	608	200	672	300	736	800
545	350	609	600	673	350	737	450
546	200	610	300	674	350	738	300
547	250	611	600	675	700	739	1200
548	300	612	250	676	450	740	1200
549	900	613	250	677	250	741	200
550	250	614	450	678	400	742	250
551	150	615	1600	679	300	743	2000
552	450	616	400	680	1100	744	300
553	250	617	400	681	200	745	700
554	450	618	300	682	450	746	900
555	300	619	400	683	450	747	600
556	250	620	350	684	350	748	350
557	350	621	300	685	700	749	600
558	1800	622	300	686	1900	750	1400
559	400	623	600	687	1000	751	2000
560	700	624	350	688	350	752	2000
561	600	625	300	689	350	753	2000
562	250	626	450	690	200	754	300
563	450	627	350	691	300	755	1600
564	700	628	250	692	1800	756	1900

Table 4.8 (cont'd)

Pipe No	Diameter (mm)	Pipe No	Diameter (mm)	Pipe No	Diameter (mm)	Pipe No	Diameter (mm)
757	1900	772	250	787	600	801	300
758	1900	773	450	788	2000	802	800
759	2000	774	350	789	450	803	1500
760	1900	775	300	790	400	804	1100
761	1600	776	400	791	300	805	400
762	1900	777	600	792	500	806	1000
763	1000	778	800	793	800	807	300
764	2000	779	1200	794	700	808	500
765	2000	780	900	795	450	809	1500
766	2200	781	1300	796	1200	810	700
767	2000	782	300	797	1500	811	800
768	1800	783	300	798	600	812	400
769	1800	784	300	799	2000	813	1100
770	1400	785	450	800	2000	814	300
771	450	786	250	801	1300		

Table 4.9 Data of New York City Water Tunnel System (Rehabilitation)

Node Data		Pipe Data		
Node	Demand (ft^3/s)	Pipe	Length (ft)	Diameter (in)
1	-2,017.5	1	11,600	180
2	92.4	2	19,800	180
3	92.4	3	7,300	180
4	88.2	4	8,300	180
5	88.2	5	8,600	180
6	88.2	6	19,100	180
7	88.2	7	9,600	132
8	88.2	8	12,500	132
9	170.0	9	9,600	180
10	1.0	10	11,200	204
11	170.0	11	14,500	204
12	117.1	12	12,200	204
13	117.1	13	24,100	204
14	92.4	14	21,100	204
15	92.4	15	15,500	204
16	170.0	16	26,400	72
17	57.5	17	31,200	72
18	117.1	18	24,000	60
19	117.1	19	14,400	60
20	170.0	20	38,400	60
		21	26,400	72

Table 4.10 Market Pipe Sizes and Pipe Costs: New York City Water Tunnel (Rehabilitation)

Option No.	Diameter (in)	Cost ($/ft)
1	0	0
2	36	93.5
3	48	134
4	60	176
5	72	221
6	84	267
7	96	316
8	108	365
9	120	417
10	132	469
11	144	522
12	156	577
13	168	632
14	180	689
15	192	746
16	204	804

Table 4.11 Optimal Solutions Resulting from Various Techniques: New York City Water Tunnel (Rehabilitation)

Pipe No	Pipe Diameters (in)				
	Dandy et al. (1996) GA1	Lippai et al. (1999) Evolver NYD1.XLS	Eusuff and Lansey (2003) SFLA	Maier et al. (2003) ACOAs	SCE[a] N.O.C.=4 N.O.P =30
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
6	0	0	0	0	0
7	0	132	132	144	144
8	0	0	0	0	0
9	0	0	0	0	0
10	0	0	0	0	0
11	0	0	0	0	0
12	0	0	0	0	0
13	0	0	0	0	0
14	0	0	0	0	0
15	120	0	0	0	0
16	84	96	96	96	96
17	96	96	96	96	96
18	84	84	84	84	84
19	72	72	72	72	72
20	0	0	0	0	0
21	72	72	72	72	72
Cost ($m)	38.80	38.13*	38.13*	38.64	38.64
FEN[b]	96,750	46,016	31,267	13,928	7,650
CPU time	-	-	-	-	1min 50s

[a] Solution obtained by SCE, N.O.C. = Number of complexes and N.O.P = Number of points in each complex.
[b] Function Evaluation Number.
*Infeasible Solution (Maier et al. 2003).

Table 4.12 Pressures at Various Nodes: New York City Water Tunnel (Rehabilitation)

Node	Pressure (ft)		
	Minimum Requirement	Eusuff and Lansey (2003) SFLA	Maier et al. (2003) ACOAs & SCE
1(Source)	300	300	300
2	255	294.23	294.21
3	255	286.20	286.15
4	255	283.84	283.79
5	255	281.76	281.70
6	255	280.15	280.07
7	255	277.61	277.51
8	255	276.56	276.67
9	255	273.70	273.78
10	255	273.66	273.74
11	255	273.79	273.87
12	255	275.07	275.14
13	255	278.04	278.10
14	255	285.53	285.56
15	255	293.31	293.33
16	260	260.00	260.08
17	272.8	272.80	272.87
18	255	261.11	261.18
19	255	254.98*	255.05
20	255	260.65	260.73

*Infeasible solution when EPANET network solver was used.

CHAPTER 5

CALIBRATION OF WATER DISTRIBUTION NETWORK MODEL

5.1 INTRODUCTION

Water distribution network model is used to predict the behavior of the network under different conditions. Before using the model, its validity must be checked in order to ensure reasonable agreement between the model estimates and field observations. The validity of a computer model for analyzing, designing or improving water distribution systems depends largely on the accuracy of the input data. The simulator simply solves the equations using the supplied data. Before simulating with a computer program, the physical system of the network must be defined. The network is configured with link, nodes, tanks, pump database. The link data include pipe identification number, pipe length, pipe diameter, and pipe roughness. The node data include junction identification number, node elevation, and nodal demands. In addition, physical data for tanks, reservoir and pumps must be introduced. However, some data associated with link (roughness coefficients) and node (demands) are very difficult to collect. Because of these difficulties, the information of these two parameters is determined via model calibration. Calibration also increases the confidence of the modeler by demonstrating the ability of the model to reproduce the existing conditions. The modeler can conceive the sensitive input variables and will be careful in determining those variables. Another advantage of model calibration is that it helps in identifying the errors caused by mistakes made during the model-building process. In this study, an attempt is made to determine the pipe roughness coefficients and nodal demands of the water distribution network model.

5.2 CALIBRATING NETWORK MODEL

Model calibration deals with the adjustment of the hydraulic network parameters until the results sufficiently match the measured field data. The process is categorized into two steps: (1) comparison between the simulated and the measured pipe flows, nodal pressures, and tank water levels for known operating conditions; and (2) adjustment of network input data to decrease the differences between the predicted and observed values (Walski, 1983; Bhave, 1988). This process can be performed manually as well as automatically.

5.2.1 Manual Calibration

Manual approach is highly dependent on the experience of the modeler who calibrates the model. Values of the parameters (roughness coefficients and nodal demands) are initially assumed on the basis of field measurements. If the predicted results do not agree with the actual results, the user then adjusts the parameter values to obtain a better fit between simulated and measured flow, pressure and tank levels. The process is repeated until a satisfactory match is obtained. If no satisfactory match is found, further investigation is made to identify the discrepancies between the model and the real system. However, this manual approach is tedious and time consuming particularly when the number of calibration parameters is very large.

5.2.2 Automatic calibration

Automatic calibration methods remove the shortcomings of manual calibration and ease the evaluation (decision-making) process to a great extent. The problem is usually referred to as under-constrained problem having many more unknowns than equations. Optimization techniques can be used successfully to solve the problem.

The techniques locate the global optimum on a response surface which has numerous local optima by a systematic procedure. The search process begins with a population of solutions from the feasible space and successively adjusts the pipe roughness coefficients and nodal demands in an iterative manner. Automatic calibration method is a powerful tool which saves enormous time and improves model performance simultaneously.

5.3 METHODOLOGY

The basic idea behind the automatic calibration of water distribution network model is to use an optimization algorithm to generate pipe roughness coefficients and/or nodal demands (decision variables) within pre-specified limits and a network simulation model to evaluate the hydraulic performance. The output from the simulation model includes the numerical results for calculating the objective function. This study considers the same global optimization tool (SCE) and water network solver (EPANET) discussed in Chapter 3 for fine-tuning the network parameters.

The main goal of calibration of water distribution network model is to minimize the objective function. The objective function is the difference between the simulated and the observed data. This study aims to find the optimal pipe roughness coefficients that closely match the simulated pressure heads to the corresponding field values. During SCE calibration, the pipe roughness coefficients are generated randomly within a solution space. These roughness values may be the values used in Colebrook-White formulation, or Hazen-Williams C-factors. Individual pipe may have a roughness value or a group of pipes can be pre-selected to have a common roughness value based on the age, material and location. EPANET (hydraulic simulation program) then evaluates the hydraulics (nodal pressure) of the solution for both steady-state as well as extended period simulations. The solution is passed back to the optimization routine, where the algorithm computes the objective function, evaluates the constraints and updates the decision variables accordingly. The new decision variable is then transferred to the simulation tool again and the process is repeated until an acceptable solution is obtained. The overall process is shown in Figure 5.1.

The objective function of the problem is to minimize the root-mean-square error (*RMSE*) between the observed and predicted output. In this study, the sum of square difference between the observed and predicted pressure heads is used to calculate the objective function. The function is:

$$RMSE = [\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(AP_{it} - SP_{it})^2]^{1/2} \tag{5.1}$$

where AP_{it} and SP_{it} are respectively the actual and simulated nodal pressures at node i at time t; N is the total number of nodes at which pressure heads are measured; T is the total duration of time.

The mathematical formulation can be stated as follows:

Minimize *RMSE* (5.2)

Subjected to:

$G(H,D) = 0$, a conservation of mass and energy equation (5.3a)

$C_{min} < C(k) < C_{max}$, constraints related to design parameters (5.3b)

where $C(k)$ = pipe roughness coefficients of k^{th} pipe; C_{min} and C_{max} are lower and upper bounds of pipe roughness coefficients.

5.4 STOPPING CRITERIA FOR NETWORK MODEL CALIBRATION

The stopping criteria checked at each run are:

1. If the number of evaluations of the objective function reaches the maximum;
2. If the objective function value is less than a specified limit (usually 0.001).

Should any one of the above is met, the model is terminated.

5.5 CASE STUDIES

5.5.1 EPANET Network

The first test example (Figure 5.2) has been taken from EPANET manual (Rossman, 1993). This network is particularly chosen to check whether the proposed scheme is able to arrive at the optimal calibration parameters. The network comprises of 12 pipes, 9 junction nodes, one reservoir, one pump and an elevated water tank. The network data is given in Table 5.1. The objective is to determine a set of roughness coefficients for all pipes in the network so that the resulting pressures would closely mimic their field counterparts. The actual roughness coefficient (Hazen-Williams C factor) for all pipes is 100. A hydraulic analysis is performed using this roughness parameter for an extended period simulation to obtain a set of values of nodal pressures at a particular node 9, which are later used as the actual nodal pressures to reproduce the roughness coefficients of the pipes. Table 5.3 shows the actual nodal pressures for 24 hours time period.

The analysis is preformed using a lower limit of 50 and an upper limit of 150 for the decision variables (roughness coefficients). The following SCE parameters are used: the number of complexes = 12, number points in each complex = 25, number points in each sub-complex = 13, total number of population = 300, and the maximum number of function evaluation allowed = 15,000. The initial value of roughness is assumed as 90 for all pipes. Ten runs are performed using different initial seed values. The result shows that SCE finds the optimum solution (Table 5.2) with pressure heads exactly matches the actual values (Table 5.3). SCE requires 7,376 function evaluations and a CPU time of only 1 minute and 40 sec to produce this better fit. Figure 5.3 depicts the reducing *RMSE* value with the increasing function evaluation number. The difference between the actual and the simulated pressure heads at node 9 is shown in Figure 5.4 over 24 hours duration.

5.5.2 Ormsbee and Wood (1986) Pipe Network

The second example (Figure 5.5) was presented by Ormsbee and Wood (1986). Table 5.4 illustrates the network configuration. It consists of 21 pipes and 13 junction nodes, three elevated storage tanks and a pump. The actual pressure heads for nodes 6, 8, 10, and 13 are considered for roughness factors calculation and are given in Table 5.5. Greco and Giudice (1999) also solved this network to find the most appropriate roughness coefficients. The pressure head obtained at test nodes by Greco and Giudice (1999) and Ormsbee and Wood (1986) are shown in Table 5.5.

In the present study, the program is run with the following parameters: the number of complexes = 4, number points in each complex = 20, number points in each sub-complex = 10, total number of population = 80, and the maximum number of function evaluations allowed = 4,000. The model improved the pressure heads at nodes 6 and 8 (Table 5.5) which are very much close to the original value. A good match (Figure 5.6) between the actual and simulated pressure heads is obtained only after 1,315 evaluations of the objective function; this is equivalent to 22 sec computational time in the same PC.

5.6 CONCLUSION

Water distribution network model is calibrated to find the most appropriate network parameters (pipe roughness coefficients and nodal demands) so that the hydraulic performance closely mimics the field condition. However, optimal calibration is not an easy task due to the nonlinear objective function and numerous local minima exist in the solution space. Many conventional techniques do not guarantee optimal solutions. In this study, SCE algorithm is applied together with EPANET hydraulic network solver to determine the optimal network parameters. Results show that SCE performs efficiently in cases of steady-state as well as extended period simulations.

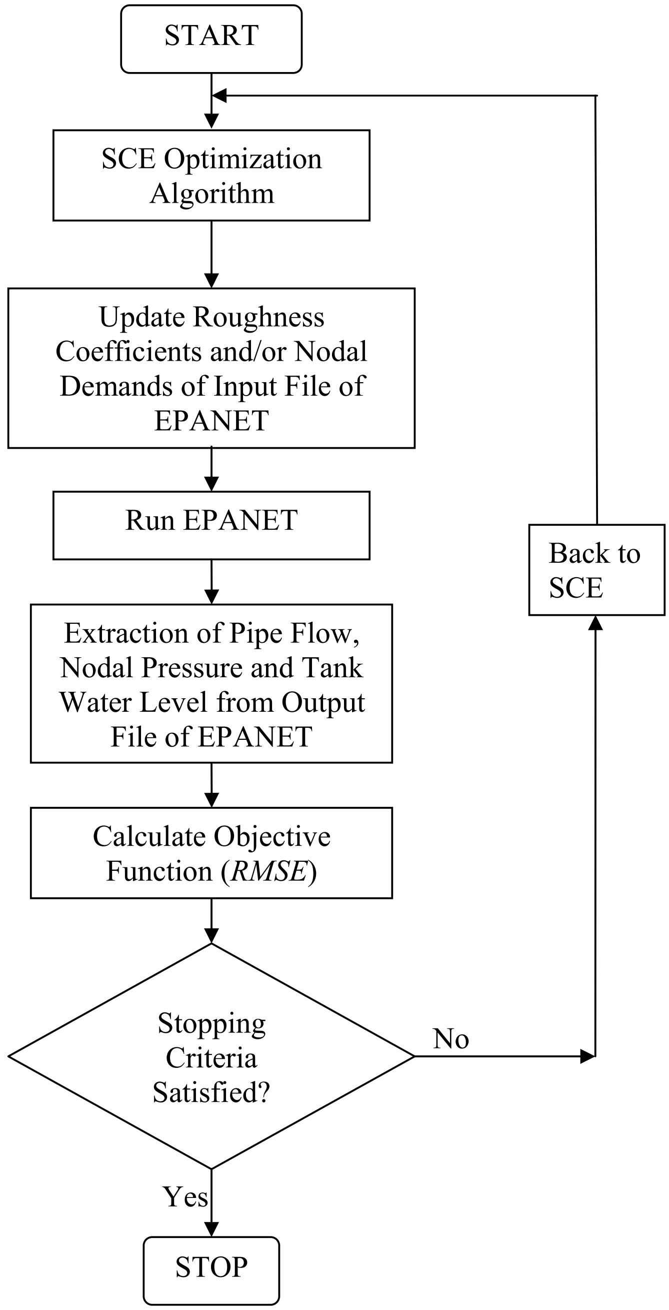

Figure 5.1 Flow Chart of a Calibration Problem

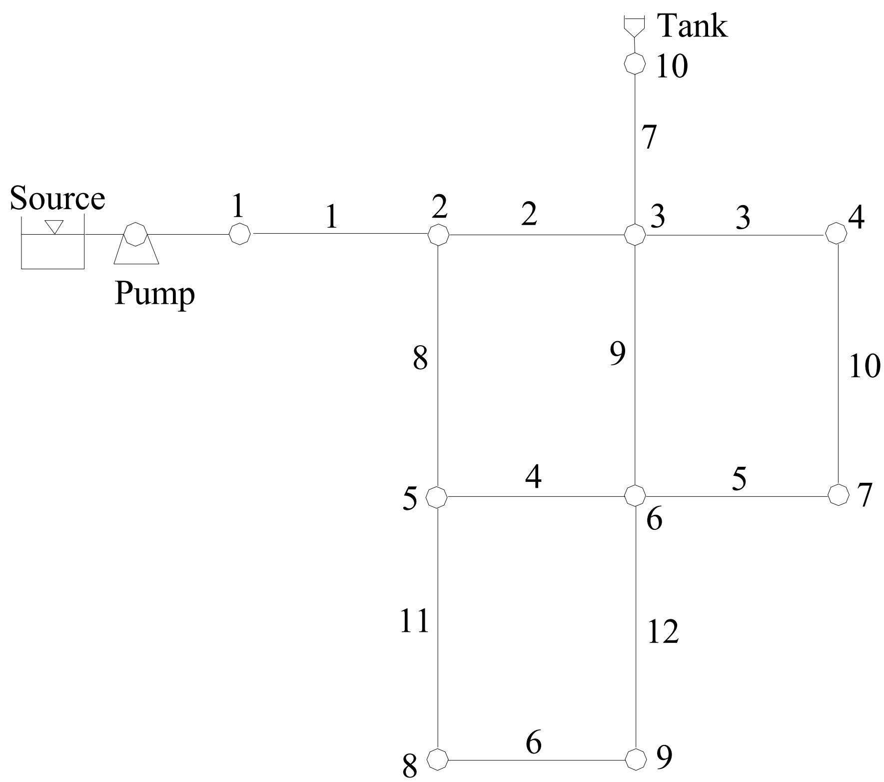

Figure 5.2 EPANET Network Problem

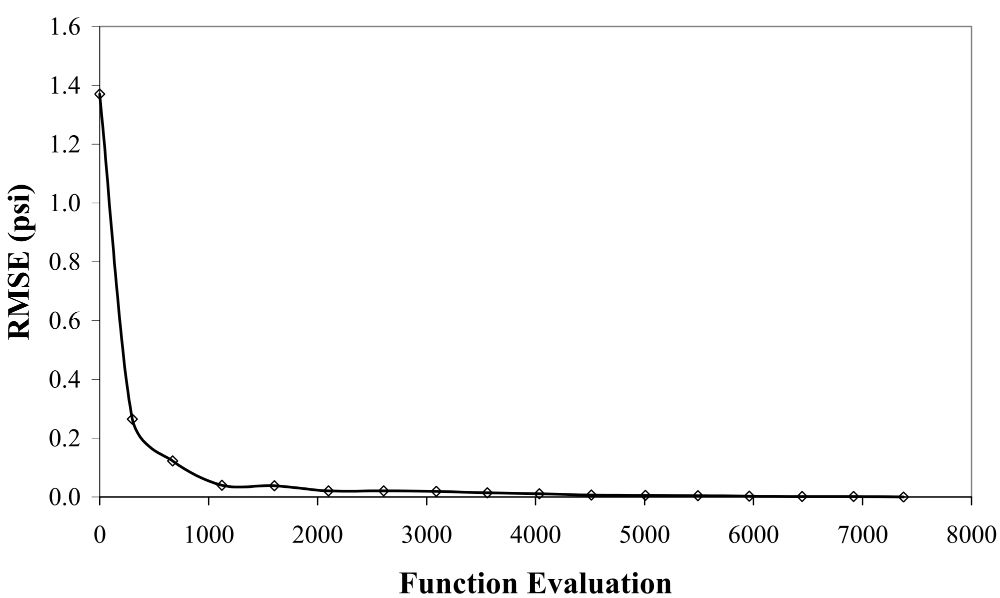

Figure 5.3 Evolution of RMSE with Function Evaluations

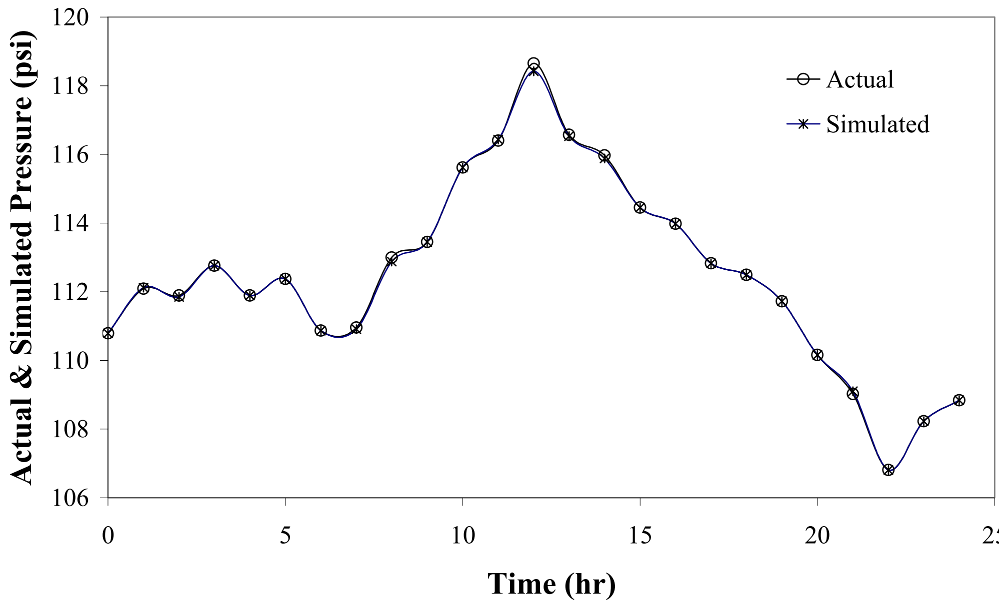

Figure 5.4 Variation of Actual and Simulated Pressure at Node 9 over Time

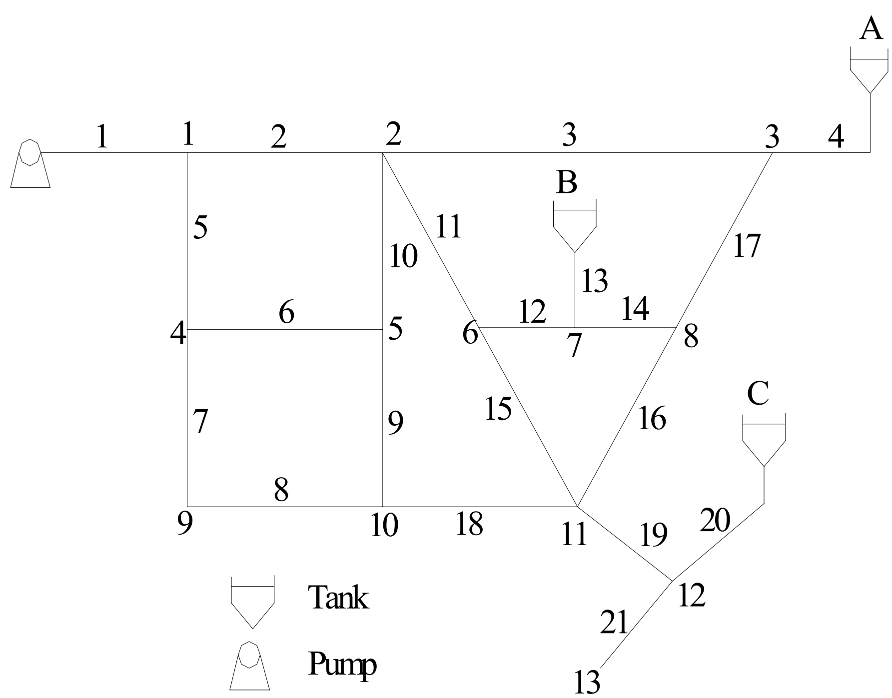

Figure 5.5 Ormsbee and Wood (1986) Pipe Network Problem

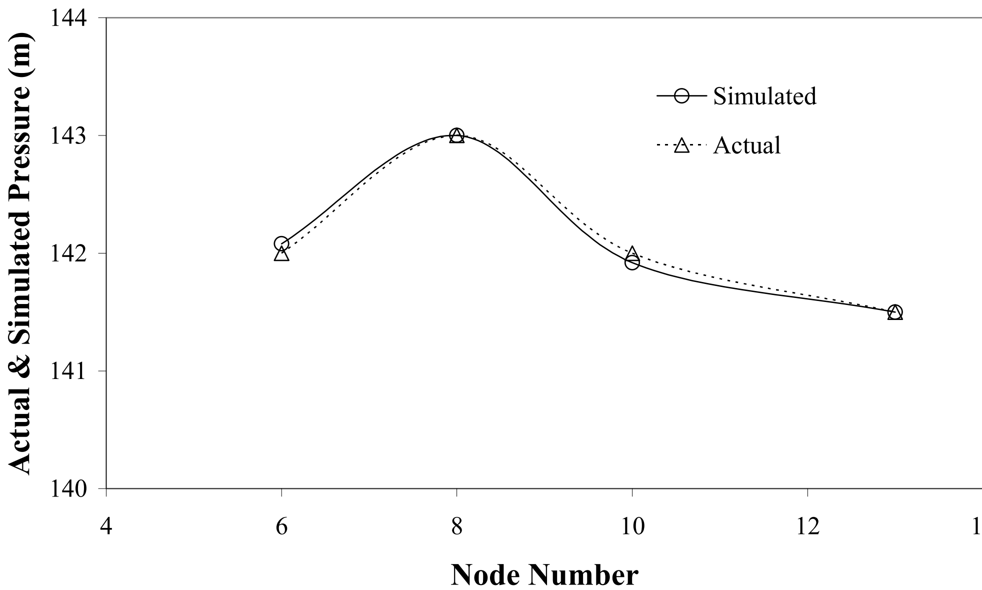

Figure 5.6 Actual and Simulated Pressures at Different Nodes

Table 5.1 EPANET Network Basic Data

Pipe Number	Starting Node	Ending Node	Length (ft)	Diameter (in)	Node Number	Demand (GPM)
1	1	2	10,530	18	1	0
2	2	3	5,280	14	2	150
3	3	4	5,280	10	3	150
4	5	6	5,280	10	4	100
5	6	7	5,280	12	5	150
6	8	9	5,280	6	6	200
7	3	10	200	18	7	150
8	2	5	5,280	10	8	100
9	3	6	5,280	12	9	100
10	4	7	5,280	8		
11	5	8	5,280	8		
12	6	9	5,280	6		

Table 5.2 Actual and Measured Pipe Roughness Coefficients

Pipe No	Roughness Coefficients	
	Actual	Simulated
1	100	99.74
2	100	100.58
3	100	100.66
4	100	101.41
5	100	101.87
6	100	101.47
7	100	101.44
8	100	99.12
9	100	97.53
10	100	100.62
11	100	104.20
12	100	98.78

Table 5.3 Actual and Simulated Nodal Pressure at Node 9

Time (hr)	Pressure (psi)	
	Actual	Simulated
0.00	110.79	110.79
1.00	112.09	112.12
2.00	111.89	111.85
3.00	112.76	112.76
4.00	111.89	111.89
5.00	112.37	112.37
6.00	110.87	110.87
7.00	110.96	110.91
8.00	113.00	112.88
9.00	113.45	113.45
10.00	115.62	115.62
11.00	116.40	116.43
12.00	118.65	118.42
13.00	116.57	116.53
14.00	115.97	115.88
15.00	114.45	114.45
16.00	113.98	113.98
17.00	112.83	112.83
18.00	112.49	112.49
19.00	111.72	111.72
20.00	110.16	110.16
21.00	109.02	109.10
22.00	106.81	106.81
23.00	108.23	108.23
24.00	108.84	108.84

Table 5.4 Ormsbee and Wood (1986) Pipe Network Basic Data

Pipe Number	Starting Node	Ending Node	Length (m)	Diameter (mm)	Node Number	Demand (L/s)
1	0	1	300	300	2	40
2	1	2	250	250	3	40
3	2	3	450	250	6	80
4	3	0	300	200	8	40
5	1	4	150	250	9	60
6	4	5	250	200	11	100
7	4	9	170	250	13	20
8	9	10	250	250		
9	10	5	170	200		
10	2	5	150	200		
11	2	6	160	200		
12	6	7	140	200		
13	0	7	80	200		
14	7	8	140	200		
15	6	11	300	200		
16	8	11	300	250		
17	8	3	200	250		
18	10	11	200	250		
19	11	12	300	150		
20	0	12	200	150		
21	12	13	175	150		

Table 5.5 Measured and Calibrated Nodal Pressures

Node	Measured Pressure (m)	Calibrated Pressure (m)		
		Ormsbee and Wood (1986)	Greco and Giudice (1999)	SCE
6	142.00	141.90	141.97	142.08
8	143.00	142.69	142.72	143.00
10	142.00	142.00	142.00	141.92
13	141.50	141.50	141.50	141.50

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 CONCLUSIONS

Water, which is a fundamental need for human beings, is fed into the water distribution network to transport it to the people of the country. The country people demand the required amount of water at their hand with adequate head. Water managers are responsible to meet up the people's demand with the establishment of an economically feasible and cost effective network. They, generally, encounter two types of practical problems which need to be solved efficiently. One is the design of a new water distribution network and the other is the rehabilitation of an existing network. New network is needed to be installed in the newly developed areas, whereas the existing network is to be rehabilitated due to population growth, leakage, breakage of the pipes. Both the problems involve many complexities which are described in Chapter 1. The aim of this study is to use an evolutionary algorithm to design optimization of water distribution network and to determine the network parameters by calibrating the network model.

6.1.1 DETERMINING OPTIMAL PIPE SIZES

Design or rehabilitation of water distribution network can be performed manually or automatically. Manual design is obviously very cumbersome and, above all, the performance depends on the experience of the modeler. Moreover, it is very time consuming to determine the least cost solution satisfying user specified constraints. In contrast, automatic design scheme overcomes the tedious manual process. Automatic process couples an optimization tool and a hydraulic network simulation model. Many traditional and heuristic optimization tools have been developed and applied to the design and rehabilitation of water distribution network which are discussed in Chapter 2.

Traditional optimization tools discussed in Section 2.2.2 include linear programming (LP), non-linear programming (NLP), and dynamic programming (DP). Some traditional algorithms are unable to arrive at global minima and need extensive computational effort to find even the local optimum. In addition, they cannot operate with discrete variables. Since PC time increases exponentially with the number of pipes considered, the application of traditional optimization algorithms is usually limited to smaller network only.

The widely used heuristic algorithms such as Genetic Algorithm (GA), Simulated Annealing (SA), Shuffled Frog Leaping Algorithm (SFLA), Ant Colony Optimization Algorithms (ACOAs), GLOBE, etc. perform satisfactorily in the design and rehabilitation of water distribution networks. These techniques are used due to their potential in offering good solutions of complicated combinatorial optimization problems. However, in many instances, they require large functional evaluations and running time to determine the optimal solution of the water distribution network problems.

This study demonstrated the feasibility of Shuffled Complex Evolution (SCE) in several designs of water distribution networks. As discussed in Section 3.3, SCE yields a delicate balance between exploration and exploitation than the standard GA. It searches in different directions within the feasible space; SCE is based on the Nelder and Mead Simplex Method. To apply SCE, the dimension of the original SCE was first increased for higher dimensional problems. In this study SCE was linked with a public domain simulation model, EPANET, and then applied to designs of the water distribution networks. The model was presented in Section 3.4.

As presented in Section 4.2.2, consideration of pressure deficit is utmost essential to arrive at the optimal solution in design and rehabilitation of water distribution networks. Nodal pressure deficits are incorporated into the objective function as penalties. Conventionally, the network problem is solved by minimizing the total cost comprising the network cost and the ‘penalty cost’ or penalty function. An appropriate penalty factor must be assigned into the penalty function. The penalty factor should be large enough to prevent the final solution from being infeasible and small enough not to prevent adequate exploration of the search space. A trial and error method is used to select an effective weighting factor. This study considers the penalty factor as a variable and consequently removes the necessity of a trial-and-error selection approach.

The coupled model (SCE-EPANET) was first applied to designs of two new networks (Section 4.5.1 and Section 4.5.2) used widely in the literature; this allows one to compare performance resulting from various techniques. SCE solved the problems more efficiently than GA, SA, GLOBE, and SFLA as proposed by other researchers. Besides these two simple networks, design of a large scale water distribution network at Ecuador is also considered in Section 4.5.3. In that water supply system, each pipe is considered as a variable; there are a total of 814 variables. Considering there are twenty four commercial pipe sizes, the possible number of combinations is prohibitively large for a trial-and-error approach. SCE intelligently searched only a certain number of combinations to arrive at a feasible optimal region in the solution space. To increase the convergence chances of SCE in the optimal region and to reduce the chance of being trapped in the local optima, some points resulting from each and from the last generations of SCE of a run are included in the subsequent run. As a result, the solution of the final run is significantly more optimal.

To avoid selection and inclusion of population of points from previous to the subsequent runs manually, Kohonen Neural Network (KNN) is applied to do the automatic selection of the different representative points covering different regions in the feasible domain. KNN removes some percentage of randomness of SCE in generating the initial points of the subsequent runs. With the KNN based selection, SCE was shown to yield lower network cost for the Ecuador water distribution network problem. The model shows the robustness as illustrated in Section 4.6 in optimizing the optimal rehabilitation options of a widely used New York Water City Tunnel problem. Alternative options were suggested in an efficient manner, compared to those of other heuristic techniques, to cope with the higher demand at a certain part of the water network.

The main concern in the design and rehabilitation of water distribution network is to achieve the least-cost solution. However, the optimal solution may be infeasible for a number of reasons. On the other hand, the suboptimal solution may be a little more expensive, but it may provide significantly better pressure characteristics than the optimal solution, though both solutions meet the pressure requirement. The suboptimal solution guarantees surplus pressure at some of the demand nodes. So, it may be of interest to invest more capital to achieve adequate pressure for future higher demand. SCE yields a set of feasible solutions in the final generation which is very useful to the decision maker to select a suitable solution of interest based on the budget and other design criteria.

Since the probabilistic approaches are involved in the algorithm, SCE may not ensure the achievement of an optimum solution every time. However, it starts exhaustive exploration and shows its potential in converging into the global region using the latest information without destroying the local optima especially in higher dimensional problems.

6.1.2 DETERMINING NETWORK PARAMETERS

In order to apply the model in the rehabilitation of water distribution network, the input network data especially pipe roughness coefficients and nodal demands should be precise. Another reason is that the roughness of the pipes increases over time and a periodic estimation of this parameter should be performed for optimal management of water delivery systems. However, due to economic and other constraints, the optimal values of these parameters cannot be determined easily. The parameters are determined through model calibration. Section 5.2 discussed the complexities in the calibration of the network model. The model having the same optimization algorithm was used to overcome the difficulties and to determine accurate network parameters. The methodology described in Section 5.3 minimized the objective of root mean square error between the actual and simulated pressures over steady-state as well as extended period simulation. The study showed that SCE was able to locate the optimal network parameters in different case studies with reasonably close agreement between the simulated and the field results. Thus, this gives assurance of the model's reliability.

6.2 RECOMMENDATIONS FOR FURTHER STUDY

The following are some suggestions relevant to future works in water distribution network:

1. Modification of SCE algorithm based on crossover and mutation mechanisms. In SCE, a local search technique namely Nelder and Mead simplex method (NMSM) is used to evolve a complex of points. However, NMSM may be too cumbersome in reaching the global minima for cases with high dimensional water distribution network problem. It may converge into some regions of the search space. This may result in the algorithm trapped in local optima. After evaluating various points in complexes through competitive complex evolution (CCE), introducing the crossover and mutation operations on best points from the complexes may prevent premature convergence and hence not getting trapped in local optima.
2. Development of multi-objective shuffled complex evolution to generate a Pareto-front for decision alternatives which give the design engineer the flexibility to identify solutions of particular interest.
3. Design of pipe network problems considers multiple loading conditions since nodal demands are very uncertain and may vary over time. Other design variables like pump characteristics, valves, reservoir etc. should also be incorporated in the model.
4. Design of water distribution network should incorporate both steady state and transient analysis to prevent water hammer.

5. Incorporate transient analysis in the calibration of pipe network model to estimate the pipe roughness coefficients and nodal demands.
6. Coupling of Kohonen Self Organizing Map toolbox and Shuffled Complex Evolution to automate the selection process of representative points within the search space.
7. Inclusion of other sophisticated clustering techniques in identifying the best grouping process to select the representative initial population distributed over the feasible space.
8. EPANET is a commonly used network simulation tool. Other hydraulic network solvers such as MIKE NET, KYPIPE etc. should be considered in the water distribution network performance and compared with that of EPANET.

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APPENDIX A

Table A.1 EPANET Input File

```
[TITLE]
TWO-LOOP NETWORK

[JUNCTIONS]
;ID      Elev         Demand       Pattern
 2       150          100.0                          ;
 3       160          100                            ;
 4       155          120                            ;
 5       150          270                            ;
 6       165          330                            ;
 7       160          200                            ;

[RESERVOIRS]
;ID            Head          Pattern
 1             210                         ;

[TANKS]
;ID  Elevation  InitLevel  MinLevel  MaxLevel  Diameter  MinVol  VolCurve

[PIPES]
;ID     Node1   Node2   Length  Diameter     Roughness    MinorLoss    Status
 1      1       2       1000    508          130          0            Open   ;
 2      2       3       1000    508          130          0            Open   ;
 3      2       4       1000    508          130          0            Open   ;
 4      4       5       1000    508          130          0            Open   ;
 5      4       6       1000    508          130          0            Open   ;
 6      6       7       1000    508          130          0            Open   ;
 7      3       5       1000    508          130          0            Open   ;
 8      5       7       1000    508          130          0            Open   ;

[PUMPS]
;ID            Node1         Node2         Parameters

[VALVES]
;ID  Node1  Node2  Diameter  Type       Setting   MinorLoss

[TAGS]

[DEMANDS]
;Junction     Demand    Pattern    Category

[STATUS]
;ID         Status/Setting

[PATTERNS]
;ID            Multipliers

[CURVES]
;ID            X-Value       Y-Value

[CONTROLS]


[RULES]


[ENERGY]
```

Table A.2 Network Data of Irrigation Network

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
1	3	4	427	3	15.3	0
2	5	6	274	4	12.76	19.2
3	7	8	571	5	29.25	0
4	9	10	371	6	25.46	0
5	11	9	489	7	25.83	0
6	13	14	364	8	22.72	0
7	6	7	433	9	26.03	0
8	17	18	424	10	24.8	0
9	17	20	458	11	26.5	0
10	8	11	266	13	24.37	0
11	20	24	631	14	25.03	0
12	10	13	97	17	31	19.2
13	27	28	275	18	26	19.2
14	29	27	66	20	26	19.2
15	29	32	520	24	25.6	19.2
16	33	34	503	27	23	19.2
17	33	36	674	28	21.5	19.2
18	37	38	446	29	23.2	19.2
19	37	40	437	32	26.76	0
20	37	42	446	33	27.21	0
21	42	44	436	34	20.87	19.2
22	42	46	437	36	28.66	0
23	42	48	634	37	0	0
24	48	50	435	38	25.12	19.2
25	18	52	277	40	22.9	19.2
26	53	54	367	42	17.75	19.2
27	36	56	299	44	29.74	19.2
28	57	58	345	46	27	19.2
29	57	60	440	48	31.49	19.2
30	57	62	451	50	39.92	19.2
31	63	64	457	52	40.8	19.2
32	65	66	190	53	19.36	0
33	67	68	435	54	-1	0
34	69	70	437	56	29.32	0
35	69	72	440	57	20.69	19.2
36	73	69	460	58	26.96	19.2
37	73	76	442	60	17.59	19.2
38	77	78	454	62	18.48	19.2
39	77	80	609	63	2.5	19.2
40	76	77	447	64	8	19.2
41	76	84	479	65	0	0
42	85	86	449	66	20.63	0
43	84	88	436	67	5	19.2
44	89	90	96	68	8	19.2
45	89	92	123	69	22	19.2
46	92	94	487	70	25	19.2
47	92	96	330	72	37	19.2
48	96	98	296	73	25	19.2
49	96	100	537	76	20	19.2
50	68	102	453	77	25	19.2
51	103	104	224	78	22	19.2
52	105	106	198	80	30	19.2
53	107	108	398	84	21	19.2
54	109	110	1	85	0	0
55	111	112	280	86	40	19.2
56	113	114	9778	88	23.5	19.2
57	115	116	623	89	0	0
58	116	118	429	90	26.85	19.2
59	116	120	519	92	20.79	19.2
60	68	122	420	94	19.49	19.2
61	123	124	167	96	24.17	19.2
62	125	126	435	98	30.57	19.2
63	127	128	304	100	28.09	19.2
64	125	130	486	102	8	19.2
65	131	132	457	103	18.48	19.2
66	131	134	450	104	17.24	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
67	134	136	449	105	17.8	19.2
68	134	138	450	106	17.9	19.2
69	138	140	437	107	24.94	19.2
70	138	142	438	108	36	0
71	142	144	439	109	-1	0
72	142	146	902	110	0	0
73	146	148	348	111	15.62	19.2
74	146	150	442	112	14.28	0
75	134	152	435	113	0	0
76	131	154	440	114	-1	0
77	155	131	440	115	24	19.2
78	157	158	436	116	22.85	19.2
79	159	160	478	118	3.2	19.2
80	159	162	530	120	13.3	19.2
81	163	164	354	122	8	19.2
82	165	166	325	123	0	0
83	163	168	364	124	18.94	0
84	169	159	448	125	18.6	19.2
85	160	154	419	126	17.09	19.2
86	173	174	450	127	15.45	19.2
87	173	176	475	128	19.66	19.2
88	177	178	478	130	18.7	19.2
89	176	180	487	131	21.44	19.2
90	181	182	468	132	21	19.2
91	183	184	421	134	23.4	19.2
92	185	186	583	136	20.3	19.2
93	187	188	449	138	19.88	19.2
94	189	190	184	140	23.07	19.2
95	191	192	442	142	24.16	19.2
96	191	194	445	144	22.62	19.2
97	194	196	233	146	22.81	19.2
98	197	198	445	148	19.98	19.2
99	130	200	439	150	19.2	19.2
100	200	202	123	152	23.06	19.2
101	202	204	416	154	21.73	19.2
102	202	206	492	155	20.39	19.2
103	207	208	452	157	16.5	19.2
104	208	210	452	158	10.62	19.2
105	208	212	380	159	24.03	19.2
106	208	214	318	160	23.62	19.2
107	194	216	445	162	24	19.2
108	216	218	442	163	21.47	19.2
109	216	220	447	164	22.46	19.2
110	216	222	447	165	6.85	19.2
111	222	224	450	166	13	19.2
112	222	185	468	168	22.95	19.2
113	10	228	337	169	22.18	19.2
114	229	230	520	173	24	19.2
115	231	232	341	174	23.74	19.2
116	231	234	420	176	31.65	19.2
117	235	236	427	177	3.25	19.2
118	234	238	721	178	2.75	19.2
119	239	240	419	180	21.78	19.2
120	188	242	448	181	18.2	19.2
121	243	244	452	182	17.2	19.2
122	68	246	432	183	16.53	19.2
123	247	248	447	184	0	0
124	249	250	371	185	12.69	19.2
125	250	4	442	186	29.53	19.2
126	253	254	384	187	16.7	19.2
127	253	248	451	188	15.5	19.2
128	257	258	413	189	15.37	19.2
129	259	260	452	190	14.62	19.2
130	261	262	446	191	15.7	19.2
131	261	264	443	192	15.6	19.2
132	264	266	452	194	15.36	19.2
133	267	259	451	196	15.9	19.2
134	261	270	323	197	16.36	19.2
135	271	272	444	198	26.87	19.2
136	273	274	438	200	23.3	19.2
137	275	276	444	202	20.36	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
138	277	278	446	204	24.2	19.2
139	278	276	442	206	19.39	19.2
140	278	282	452	207	18.04	19.2
141	283	275	448	208	17.9	19.2
142	282	286	441	210	26.3	19.2
143	276	288	428	212	28.57	19.2
144	270	290	499	214	18.2	19.2
145	291	292	384	216	14.4	19.2
146	293	294	450	218	15.5	19.2
147	295	296	350	220	15.89	19.2
148	295	298	460	222	13.81	19.2
149	298	300	441	224	15.3	19.2
150	105	302	510	228	24.66	19.2
151	298	304	445	229	15.74	19.2
152	305	306	326	230	21.87	19.2
153	307	305	465	231	13.26	19.2
154	295	310	454	232	26.45	19.2
155	311	295	450	234	16.4	19.2
156	311	314	449	235	23.92	19.2
157	315	311	447	236	21.44	19.2
158	315	318	540	238	22.84	19.2
159	319	320	447	239	3.8	19.2
160	286	322	242	240	3.7	19.2
161	282	324	438	242	14.01	19.2
162	278	326	426	243	15.24	19.2
163	271	181	460	244	15.7	19.2
164	181	330	443	246	8	19.2
165	330	332	450	247	14.1	19.2
166	333	334	450	248	17	19.2
167	335	333	370	249	30.45	19.2
168	337	338	345	250	12.6	19.2
169	337	340	263	253	14.7	19.2
170	340	342	481	254	18.4	19.2
171	340	344	487	257	11.61	19.2
172	315	346	517	258	-1	0
173	347	348	442	259	11.93	19.2
174	349	63	436	260	12.98	19.2
175	166	352	367	261	28.34	19.2
176	353	354	432	262	13.8	19.2
177	355	356	312	264	20.3	19.2
178	357	358	444	266	22.79	19.2
179	359	110	210	267	11.95	19.2
180	361	362	269	270	14.54	19.2
181	361	364	399	271	17.52	19.2
182	364	366	269	272	15.98	19.2
183	364	368	517	273	17	19.2
184	186	370	443	274	0	0
185	371	372	487	275	18.69	19.2
186	189	243	445	276	22.04	19.2
187	190	376	446	277	18.78	19.2
188	246	378	420	278	18.8	19.2
189	246	380	426	282	20.21	19.2
190	4	242	460	283	21.1	19.2
191	383	384	457	286	21.32	19.2
192	385	239	467	288	21.84	19.2
193	387	3	10	290	26.2	19.2
194	259	390	452	291	10.81	19.2
195	383	392	452	292	14.04	19.2
196	267	257	474	293	3.87	19.2
197	395	396	462	294	3.49	19.2
198	397	398	461	295	22.46	19.2
199	399	275	362	296	23.35	19.2
200	401	402	440	298	20.23	19.2
201	401	404	444	300	23.39	19.2
202	405	406	439	302	10.3	19.2
203	405	401	454	304	21.99	19.2
204	405	410	437	305	25.66	19.2
205	411	406	433	306	24.46	19.2
206	413	414	316	307	12.8	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
207	405	416	434	310	21.87	19.2
208	417	418	462	311	25.96	19.2
209	406	420	451	314	22.9	19.2
210	384	422	462	315	27.02	19.2
211	110	113	0.72	318	29	19.2
212	417	413	441	319	14.12	19.2
213	414	428	502	320	29.23	19.2
214	305	430	457	322	20.03	19.2
215	63	178	425	324	21.03	19.2
216	63	434	504	326	20.3	19.2
217	435	436	468	330	15.93	19.2
218	436	438	444	332	15.51	19.2
219	67	440	431	333	14.11	19.2
220	430	292	451	334	15.21	19.2
221	443	444	502	335	15.8	19.2
222	444	291	559	337	22.02	19.2
223	444	448	202	338	19.77	19.2
224	307	450	276	340	24.17	19.2
225	307	452	443	342	23.5	19.2
226	452	454	453	344	26.18	19.2
227	452	456	258	346	28.97	19.2
228	457	458	457	347	21.31	19.2
229	459	457	460	348	19.81	19.2
230	461	462	462	349	2.52	19.2
231	461	464	459	352	7.32	19.2
232	464	466	448	353	6.73	19.2
233	467	468	670	354	6.45	19.2
234	469	470	429	355	7.98	19.2
235	471	472	444	356	6.6	19.2
236	473	474	447	357	7.33	19.2
237	473	476	452	358	7	19.2
238	473	478	435	361	10.73	19.2
239	250	480	458	362	7.23	19.2
240	472	482	439	364	24	19.2
241	478	484	418	366	11.7	19.2
242	469	486	436	368	23.83	19.2
243	486	488	363	370	13.4	19.2
244	486	105	254	371	25	19.2
245	106	492	441	372	12.3	19.2
246	493	494	444	376	18.88	19.2
247	106	494	452	378	8	19.2
248	497	494	439	380	8	19.2
249	492	467	397	383	13.05	19.2
250	501	502	295	384	14.4	19.2
251	267	504	443	385	3.43	19.2
252	111	506	165	387	15.3	19.2
253	507	508	427	390	12.16	19.2
254	509	510	510	392	18.9	19.2
255	509	512	468	395	13.17	19.2
256	513	514	444	396	15.99	19.2
257	114	516	1	397	19	19.2
258	517	518	442	398	12.42	19.2
259	434	67	522	399	28.08	19.2
260	521	385	453	401	13.67	19.2
261	523	524	447	402	14.78	19.2
262	525	526	446	404	13.67	19.2
263	525	395	436	405	11.93	19.2
264	524	530	474	406	11.04	19.2
265	524	532	442	410	12.39	19.2
266	532	534	448	411	11.25	19.2
267	532	536	456	413	11.28	19.2
268	525	538	419	414	14.04	19.2
269	525	517	450	416	13.04	19.2
270	532	542	448	417	11.41	19.2
271	542	544	453	418	12.68	19.2
272	542	546	443	420	11.16	19.2
273	542	548	451	422	12.92	19.2
274	548	550	435	428	28.5	19.2
275	548	552	451	430	10.53	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
276	548	554	449	434	2.49	19.2
277	554	556	438	435	4.34	19.2
278	554	558	458	436	3.13	19.2
279	554	560	448	438	2.46	19.2
280	560	562	440	440	2.32	19.2
281	560	564	450	443	21.82	19.2
282	560	566	443	444	13.03	19.2
283	566	568	448	448	22.46	19.2
284	566	570	451	450	25	19.2
285	566	572	446	452	19.95	19.2
286	572	574	438	454	17.76	19.2
287	572	576	430	456	20.41	19.2
288	572	578	446	457	9.66	19.2
289	578	580	437	458	20.5	19.2
290	578	582	437	459	20.37	19.2
291	582	584	437	461	15	19.2
292	582	586	445	462	22.59	19.2
293	430	588	454	464	16	19.2
294	589	590	430	466	13.05	19.2
295	591	17	267	467	19.22	19.2
296	517	594	443	468	18.65	19.2
297	517	596	448	469	18.5	19.2
298	596	598	442	470	23.65	19.2
299	596	600	455	471	13.3	19.2
300	596	602	450	472	15.1	19.2
301	603	516	1	473	20.2	19.2
302	602	606	450	474	16.43	19.2
303	440	608	5404	476	19.15	19.2
304	609	610	436	478	17.95	19.2
305	609	612	440	480	13.34	19.2
306	609	614	447	482	16.8	19.2
307	614	616	448	484	19.13	19.2
308	614	618	447	486	17.87	19.2
309	614	514	456	488	27	19.2
310	514	622	451	492	16.05	19.2
311	623	624	447	493	17.09	19.2
312	625	623	445	494	19.3	19.2
313	625	628	453	497	21.17	19.2
314	623	630	438	501	6.59	19.2
315	623	507	464	502	6.53	19.2
316	507	634	448	504	11.74	19.2
317	635	634	446	506	16.5	19.2
318	637	638	233	507	11.1	19.2
319	238	640	434	508	12	19.2
320	625	642	452	509	20.2	19.2
321	643	644	446	510	11.62	19.2
322	643	646	446	512	25.65	19.2
323	625	648	443	513	16.8	19.2
324	648	650	434	514	12.12	19.2
325	648	652	440	516	0	0
326	648	654	461	517	14.4	19.2
327	654	656	452	518	13.8	19.2
328	654	658	443	521	3.44	19.2
329	654	660	444	523	12.3	19.2
330	660	472	452	524	12.72	19.2
331	660	664	445	525	14.4	19.2
332	665	666	450	526	13	19.2
333	206	668	250	530	12.5	19.2
334	669	664	440	532	11.85	19.2
335	671	672	443	534	11.58	19.2
336	352	674	376	536	12.58	19.2
337	672	676	465	538	15.4	19.2
338	676	235	443	542	11.3	19.2
339	347	680	407	544	11.25	19.2
340	676	682	444	546	17.4	19.2
341	347	684	288	548	6.6	19.2
342	348	686	447	550	11.4	19.2
343	687	688	441	552	4.2	19.2
344	366	690	445	554	10.8	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
345	372	471	443	556	10.72	19.2
346	693	694	448	558	11.12	19.2
347	695	696	464	560	10.4	19.2
348	165	698	437	562	9.9	19.2
349	699	700	447	564	10.9	19.2
350	701	702	282	566	11.42	19.2
351	703	704	435	568	10.62	19.2
352	264	706	457	570	11.6	19.2
353	707	708	469	572	11.81	19.2
354	709	710	459	574	8	19.2
355	711	712	615	576	12.65	19.2
356	713	714	432	578	12.72	19.2
357	707	710	450	580	12.5	19.2
358	717	718	411	582	10.65	19.2
359	719	720	309	584	16.89	19.2
360	266	722	287	586	14.58	19.2
361	665	724	458	588	8.17	19.2
362	608	726	451	589	3.73	19.2
363	727	728	454	590	4.54	19.2
364	727	730	458	591	0	0
365	727	732	452	594	15	19.2
366	732	734	443	596	14	19.2
367	732	736	454	598	13	19.2
368	737	738	461	600	1.6	19.2
369	738	727	446	602	13.2	19.2
370	608	742	412	603	-1	0
371	456	744	202	606	8.2	19.2
372	745	746	455	608	-1	19.2
373	746	748	447	609	13.2	19.2
374	746	750	446	610	11.26	19.2
375	751	752	448	612	13.1	19.2
376	228	754	169	614	3.1	19.2
377	755	756	496	616	11.88	19.2
378	608	758	483	618	13.3	19.2
379	513	760	385	622	11.12	19.2
380	756	762	242	623	10.9	19.2
381	182	474	436	624	11.4	19.2
382	765	766	432	625	11.9	19.2
383	765	701	441	628	11.6	19.2
384	638	703	496	630	10.4	19.2
385	771	700	357	634	7.2	19.2
386	189	774	445	635	1.2	19.2
387	775	387	481	637	7.4	19.2
388	777	778	505	638	10.53	19.2
389	779	780	448	640	29	19.2
390	123	183	499	642	11.4	19.2
391	638	784	217	643	13.2	19.2
392	758	786	413	644	13.1	19.2
393	779	788	455	646	11.5	19.2
394	516	790	94	648	13.1	19.2
395	788	792	456	650	13	19.2
396	788	794	445	652	13.2	19.2
397	222	796	348	654	14.54	19.2
398	765	699	442	656	13.76	19.2
399	799	665	460	658	14	19.2
400	801	665	442	660	16.9	19.2
401	803	804	452	664	17.8	19.2
402	803	806	448	665	11.52	19.2
403	806	808	452	666	0	0
404	806	810	453	668	22.54	19.2
405	806	812	440	669	18.5	19.2
406	812	814	442	671	17.17	19.2
407	812	816	449	672	18.9	19.2
408	812	818	447	674	14.5	19.2
409	818	820	433	676	20.22	19.2
410	818	822	450	680	21.4	19.2
411	818	824	456	682	20.6	19.2
412	824	826	443	684	21.1	19.2
413	824	828	447	686	19.08	19.2
414	824	830	439	687	6.12	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
415	830	832	418	688	5.96	19.2
416	833	584	468	690	17.76	19.2
417	835	836	311	693	22.7	19.2
418	837	838	264	694	21.9	19.2
419	839	840	348	695	23.1	19.2
420	841	842	501	696	22.9	19.2
421	843	609	434	698	8.54	19.2
422	845	846	437	699	11.2	19.2
423	847	848	253	700	11.2	19.2
424	849	850	462	701	10.49	19.2
425	851	852	447	702	11.37	19.2
426	853	838	454	703	9.71	19.2
427	836	833	143	704	10.52	19.2
428	857	858	494	706	31.32	19.2
429	859	858	228	707	9	19.2
430	778	862	531	708	5.31	19.2
431	14	29	367	709	7	19.2
432	836	866	334	710	7.35	19.2
433	32	33	205	711	8.13	19.2
434	56	870	697	712	8.4	19.2
435	640	872	553	713	4.91	19.2
436	873	874	583	714	5.15	19.2
437	801	803	455	717	4.73	19.2
438	803	878	450	718	4.1	19.2
439	801	880	450	719	20.31	0
440	881	745	445	720	20.03	0
441	745	732	438	722	16.69	19.2
442	745	886	439	724	10.81	19.2
443	801	888	452	726	-1	19.2
444	504	398	427	727	9.51	19.2
445	891	892	450	728	9.74	19.2
446	891	894	444	730	10.26	19.2
447	895	891	457	732	8.96	19.2
448	897	898	448	734	9.45	19.2
449	898	788	439	736	8.92	19.2
450	898	891	448	737	10.6	19.2
451	898	904	437	738	11.12	19.2
452	895	906	455	742	-1	19.2
453	762	908	332	744	21.41	19.2
454	638	910	521	745	8.72	19.2
455	234	912	420	746	8.08	19.2
456	320	276	443	748	8.56	19.2
457	915	916	454	750	8.07	19.2
458	916	918	447	751	8.21	19.2
459	916	703	444	752	7.96	19.2
460	921	922	441	754	28.99	19.2
461	746	751	446	755	11.35	19.2
462	925	398	446	756	11.28	19.2
463	927	779	447	758	5	19.2
464	927	930	452	760	12.7	19.2
465	931	932	449	762	11.79	19.2
466	933	934	438	765	11.2	19.2
467	933	936	453	766	10.6	19.2
468	921	938	460	771	15.16	19.2
469	918	933	438	774	14.99	19.2
470	922	942	432	775	6.2	19.2
471	833	842	692	777	21.35	19.2
472	942	933	454	778	19.06	19.2
473	942	948	442	779	7.68	19.2
474	949	927	467	780	8.2	19.2
475	931	952	452	784	10.19	19.2
476	687	954	445	786	5	19.2
477	687	956	447	788	8.62	19.2
478	956	851	425	790	18.49	0
479	956	960	443	792	8.9	19.2
480	956	962	446	794	8.6	19.2
481	931	687	448	796	18.3	19.2
482	927	931	447	799	11.62	19.2
483	967	968	467	801	10.2	19.2
484	967	970	431	803	9.4	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
485	967	972	445	804	10.1	19.2
486	972	974	436	806	9.4	19.2
487	972	976	448	808	8.75	19.2
488	758	978	454	810	10.2	19.2
489	979	980	1	812	9.15	19.2
490	981	358	470	814	8.3	19.2
491	981	984	434	816	9.8	19.2
492	758	986	461	818	9.4	19.2
493	987	988	432	820	8.72	19.2
494	987	354	434	822	9.9	19.2
495	987	992	452	824	9.8	19.2
496	992	356	458	826	10.6	19.2
497	992	996	449	828	9.15	19.2
498	992	998	451	830	10.3	19.2
499	998	1000	449	832	8.9	19.2
500	998	1002	452	833	20.87	19.2
501	998	714	453	835	10.1	19.2
502	714	1006	464	836	10.81	19.2
503	708	1008	445	837	8.49	19.2
504	713	1010	473	838	8.3	19.2
505	1011	1012	439	839	5.2	19.2
506	1013	1014	448	840	13.44	19.2
507	1013	714	450	841	22.45	19.2
508	972	1018	441	842	24	19.2
509	1018	1020	459	843	0	0
510	1018	1022	444	845	8	19.2
511	1018	1024	460	846	8.9	19.2
512	1024	1026	439	847	8.2	19.2
513	1024	1028	440	848	13.3	19.2
514	1024	1030	442	849	8.12	19.2
515	1030	1032	462	850	9.4	19.2
516	1030	1034	445	851	6.87	19.2
517	1030	1036	459	852	3.9	19.2
518	751	1038	446	853	14.67	19.2
519	751	1040	450	857	23	19.2
520	1040	1042	443	858	13.09	19.2
521	1040	1044	449	859	13.29	19.2
522	1040	1046	435	862	28.44	19.2
523	1046	1048	443	866	12.74	19.2
524	1046	1050	460	870	21.8	0
525	1046	1052	451	872	21.96	19.2
526	1052	1054	468	873	18.9	19.2
527	1052	849	445	874	30.19	19.2
528	1052	1058	448	878	9.3	19.2
529	1058	1060	431	880	10.4	19.2
530	1058	845	454	881	8.41	19.2
531	1058	501	442	886	8.8	19.2
532	501	853	462	888	10.3	19.2
533	220	210	643	891	9.85	19.2
534	127	458	458	892	9.4	19.2
535	127	1072	442	894	9.7	19.2
536	1073	873	402	895	0	0
537	842	848	203	897	9.2	19.2
538	874	1078	188	898	9.2	19.2
539	504	530	421	904	9.4	19.2
540	848	857	258	906	9.79	19.2
541	857	459	559	908	9.93	19.2
542	839	586	447	910	10.3	19.2
543	703	1088	454	912	28	19.2
544	918	1090	311	915	9.6	19.2
545	918	1092	452	916	8.9	19.2
546	1093	921	302	918	8.73	19.2
547	779	1096	454	921	7.4	19.2
548	1097	358	450	922	6.5	19.2
549	1099	981	482	925	10.62	19.2
550	586	1102	335	927	7.5	19.2
551	755	1104	290	930	6.4	19.2
552	1105	1106	439	931	6.3	19.2
553	1012	1106	451	932	7.3	19.2
554	1109	1106	445	933	8	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
555	1111	1112	447	934	8.1	19.2
556	1034	1114	456	936	6.98	19.2
557	1022	1116	449	938	7.2	19.2
558	666	1118	442	942	7.18	19.2
559	588	1120	431	948	7.58	19.2
560	588	413	442	949	7.21	19.2
561	464	469	450	952	6.58	19.2
562	708	1126	483	954	4.8	19.2
563	1109	1008	447	956	5.59	19.2
564	1109	713	436	960	5.8	19.2
565	1111	1132	450	962	6.15	19.2
566	1106	1132	448	967	7.4	19.2
567	1135	1136	449	968	5.9	19.2
568	1135	1138	448	970	5.2	19.2
569	1139	1140	696	972	4.6	19.2
570	214	1142	454	974	4.45	19.2
571	206	1144	442	976	4.44	19.2
572	1145	1146	412	978	5	19.2
573	642	643	441	979	0	0
574	644	1150	499	980	-1	0
575	474	464	442	981	6.32	19.2
576	1153	1154	712	984	6.52	19.2
577	1155	1156	463	986	3.8	19.2
578	622	1155	425	987	5.75	19.2
579	606	1160	425	988	6.12	19.2
580	1144	1162	332	992	5.9	19.2
581	238	777	260	996	5.65	19.2
582	304	1166	272	998	4.76	19.2
583	230	231	479	1000	5.25	19.2
584	370	1170	448	1002	6.15	19.2
585	185	229	505	1006	5.2	19.2
586	1144	1174	154	1008	5.2	19.2
587	1175	207	462	1010	4.75	19.2
588	1174	198	261	1011	3.9	19.2
589	130	1180	441	1012	4.8	19.2
590	262	1182	447	1013	4.68	19.2
591	150	1184	468	1014	5.15	19.2
592	1185	1186	415	1018	3.59	19.2
593	372	1188	451	1020	3.85	19.2
594	1189	372	426	1022	3.72	19.2
595	152	1192	451	1024	3.39	19.2
596	162	163	365	1026	3.15	19.2
597	132	200	418	1028	3.73	19.2
598	1174	1198	846	1030	4.72	19.2
599	319	1200	616	1032	4.61	19.2
600	1139	169	342	1034	4.3	19.2
601	180	1204	638	1036	5.55	19.2
602	852	979	493	1038	8.68	19.2
603	1207	1189	475	1040	8	19.2
604	1146	1210	290	1042	6.54	19.2
605	1211	962	493	1044	6.4	19.2
606	1154	53	831	1046	7.38	19.2
607	1072	1216	453	1048	6.88	19.2
608	1217	1218	435	1050	10.2	19.2
609	176	1220	270	1052	7.81	19.2
610	1204	1222	364	1054	7.6	19.2
611	159	173	450	1058	7.5	19.2
612	842	1226	531	1060	6.92	19.2
613	858	1228	448	1072	16.89	19.2
614	760	1230	446	1073	19.49	0
615	1078	1232	202	1078	31	19.2
616	334	1234	286	1088	14.89	19.2
617	333	401	443	1090	9.89	19.2
618	420	1238	440	1092	7.64	19.2
619	333	332	455	1093	8	19.2
620	183	1242	231	1096	8	19.2
621	157	1200	452	1097	7	19.2
622	1245	1246	431	1099	5.3	19.2
623	986	1248	439	1102	13.44	19.2
624	986	1250	371	1104	11.31	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
625	248	261	452	1105	4.08	19.2
626	107	1254	43	1106	3.53	19.2
627	1255	1256	400	1109	3.87	19.2
628	986	1258	436	1111	3.2	19.2
629	1259	506	438	1112	3.82	19.2
630	243	191	450	1114	4.51	19.2
631	120	1264	766	1116	7.09	19.2
632	70	1266	449	1118	12.94	19.2
633	1267	57	337	1120	12.07	19.2
634	88	1270	405	1126	4.21	19.2
635	1270	1272	589	1132	3.27	19.2
636	1273	1274	600	1135	3.21	19.2
637	46	1276	634	1136	3.52	19.2
638	27	1278	446	1138	2.92	19.2
639	44	1280	412	1139	20.72	19.2
640	44	1282	293	1140	27.79	19.2
641	291	1284	246	1142	19.15	19.2
642	1285	1286	252	1144	35.17	19.2
643	428	461	435	1145	0	0
644	467	1290	499	1146	11.97	19.2
645	302	1292	348	1150	18.9	19.2
646	1293	1294	348	1153	19.37	0
647	1295	1296	238	1154	19.37	0
648	1295	1298	246	1155	11.57	19.2
649	319	271	434	1156	11.14	19.2
650	314	1302	325	1160	15.2	19.2
651	1303	1304	254	1162	32.7	19.2
652	318	337	503	1166	21.61	19.2
653	1307	1308	1331	1170	29	19.2
654	1303	1310	192	1174	31.08	19.2
655	1303	1312	436	1175	17.06	19.2
656	1204	1314	527	1180	20.6	19.2
657	1273	1316	255	1182	20.72	19.2
658	383	395	442	1184	20.32	19.2
659	1146	1320	191	1185	31.13	19.2
660	1132	1138	447	1186	18.89	19.2
661	1323	1324	422	1188	2.2	19.2
662	1323	1326	474	1189	15.84	19.2
663	1132	1328	438	1192	22.14	19.2
664	1329	1099	419	1198	23.45	19.2
665	1326	1332	436	1200	14.4	19.2
666	1333	1259	466	1204	20.75	19.2
667	1335	293	459	1207	17.67	19.2
668	1232	103	195	1210	10.74	19.2
669	104	1340	125	1211	6	19.2
670	686	1342	412	1216	9.93	19.2
671	62	1245	451	1217	6.5	19.2
672	60	1346	454	1218	3.6	19.2
673	24	1348	340	1220	17.27	19.2
674	1349	1350	449	1222	25.56	19.2
675	1350	1352	263	1226	23.45	19.2
676	1285	1293	452	1228	12.61	19.2
677	1293	1356	450	1230	18.08	19.2
678	674	1358	496	1232	19.53	19.2
679	1138	1360	447	1234	16.37	19.2
680	1034	717	451	1238	11.22	19.2
681	717	1364	438	1242	37.1	19.2
682	1358	357	211	1245	38.75	19.2
683	368	371	461	1246	23.37	19.2
684	1104	1370	230	1248	3.8	19.2
685	50	1273	436	1250	4.7	19.2
686	870	719	634	1254	37.23	19.2
687	717	589	436	1255	17.72	19.2
688	699	1378	431	1256	18.84	19.2
689	1378	471	479	1258	5	19.2
690	646	1382	629	1259	16.2	19.2
691	1258	1384	448	1264	8.2	19.2
692	720	1386	282	1266	23	19.2
693	589	1388	440	1267	22	19.2
694	589	521	451	1270	28	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
695	1391	1392	435	1272	28	19.2
696	1392	693	445	1273	27.53	19.2
697	693	695	455	1274	31.37	19.2
698	695	1398	431	1276	26.5	19.2
699	1398	1400	474	1278	21.57	19.2
700	666	1402	464	1280	23.8	19.2
701	1402	1404	435	1282	25.1	19.2
702	1404	1145	431	1284	25.69	19.2
703	1146	755	600	1285	26.78	19.2
704	1258	1410	388	1286	39.95	19.2
705	762	1412	154	1290	22.5	19.2
706	1386	65	97	1292	21.34	19.2
707	521	1416	441	1293	26.42	19.2
708	521	349	443	1294	26.42	19.2
709	349	294	443	1295	36	19.2
710	349	435	444	1296	39	19.2
711	1423	938	271	1298	39	19.2
712	86	1285	349	1302	25.41	19.2
713	1218	501	440	1303	37	19.2
714	1429	1118	461	1304	38.4	19.2
715	476	1432	440	1307	19.36	19.2
716	1186	1255	443	1308	1	0
717	1198	1185	410	1310	38.4	19.2
718	235	1438	433	1312	38	19.2
719	1438	1440	439	1314	18.7	19.2
720	1438	1442	449	1316	28.53	19.2
721	1442	1444	427	1320	12.8	19.2
722	1442	1446	459	1323	2.62	19.2
723	1438	1448	434	1324	3.6	19.2
724	235	1450	434	1326	3.34	19.2
725	682	348	452	1328	3.91	19.2
726	348	1454	345	1329	5.93	19.2
727	916	1456	332	1332	4.18	19.2
728	1090	1458	404	1333	15.4	19.2
729	979	1460	495	1335	2.17	19.2
730	1460	1462	503	1340	17.96	0
731	1460	1464	493	1342	18.5	19.2
732	1138	1326	456	1346	29.45	19.2
733	708	712	447	1348	33.84	19.2
734	346	1470	454	1349	0	0
735	1470	1472	455	1350	23.54	19.2
736	1472	283	368	1352	23.32	19.2
737	1230	1476	339	1356	26.42	19.2
738	1476	1478	392	1358	7.66	19.2
739	510	507	437	1360	3.23	19.2
740	512	513	405	1364	4.67	19.2
741	1483	1484	447	1370	11.7	19.2
742	1220	1483	451	1378	12.13	19.2
743	1308	1488	581	1382	13.07	19.2
744	1352	1490	411	1384	3.8	19.2
745	1491	1295	209	1386	21.1	0
746	1493	1491	220	1388	3.88	19.2
747	1294	1493	477	1391	15.87	19.2
748	1298	1303	539	1392	19.3	19.2
749	1312	1500	388	1398	22.18	19.2
750	1182	1200	463	1400	19	19.2
751	1488	1153	638	1402	11.7	19.2
752	1505	184	429	1404	10.8	19.2
753	108	1505	232	1410	5.8	19.2
754	790	1510	296	1412	11.28	19.2
755	1340	603	494	1416	3.29	19.2
756	112	187	310	1423	7.78	19.2
757	1515	111	293	1429	11.7	19.2
758	1517	1515	323	1432	19.14	19.2
759	1519	1517	241	1438	22.65	19.2
760	124	1519	123	1440	21.91	19.2
761	66	1073	182	1442	22.19	19.2
762	5	109	106	1444	18.49	19.2
763	1527	1255	185	1446	20.65	19.2
764	1529	107	113	1448	21.11	19.2

Table A.2 (cont'd)

Pipe ID	Start Node	End Node	Length	Node ID	Elevation	Demand
765	1531	54	326	1450	20.1	19.2
766	387	384	443	1454	21	19.2
767	1535	1307	670	1456	9.16	19.2
768	273	387	448	1458	9.1	19.2
769	1429	602	444	1460	7.18	19.2
770	1541	262	445	1462	6.93	19.2
771	1248	1544	517	1464	8.46	19.2
772	1545	1546	415	1470	21.89	19.2
773	1545	1548	453	1472	29.3	19.2
774	1548	1550	404	1476	22.98	19.2
775	1548	1552	431	1478	28.74	19.2
776	1548	1554	442	1483	21.38	19.2
777	1554	1556	404	1484	22.17	19.2
778	1554	1558	350	1488	19.37	0
779	1559	967	422	1490	21.33	19.2
780	980	1329	403	1491	38	19.2
781	1563	188	1	1493	39	19.2
782	1565	1566	452	1500	38	19.2
783	1567	1565	444	1505	6.76	0
784	1567	1570	462	1510	19.02	19.2
785	1567	1572	417	1515	15.38	0
786	1572	1574	449	1517	16.74	0
787	978	1576	794	1519	17.67	0
788	1535	387	9	1527	-1	0
789	1576	1545	414	1529	0	0
790	1572	1582	464	1531	0	0
791	1582	1584	455	1535	1	0
792	1582	1544	452	1541	0	0
793	981	987	438	1544	3	19.2
794	10	591	72	1545	5	19.2
795	36	37	188	1546	5	19.2
796	184	1527	1	1548	5	19.2
797	756	895	230	1550	5	19.2
798	756	910	492	1552	5	19.2
799	516	1529	1	1554	5	19.2
800	516	1531	1	1556	5	19.2
801	979	1559	1	1558	6.7	19.2
802	123	115	317	1559	0	0
803	190	1563	258	1563	0	0
804	274	1541	1	1565	5.4	19.2
805	258	274	1	1566	4.7	19.2
806	65	73	342	1567	4.2	19.2
807	65	1267	216	1570	4.9	19.2
808	103	89	206	1572	3.8	19.2
809	471	1391	448	1574	3.8	19.2
810	602	843	1	1576	5	19.2
811	660	671	440	1582	3.5	19.2
812	738	1145	451	1584	3.8	19.2
813	7	1349	121			
814	11	85	128			

Table A.3 Nodal Pressure of Irrigation Network

Node no	Pressure (m)	Node no	Pressure (m)	Node no	Pressure (m)	Node no	Pressure (m)	Node no	Pressure (m)
1	20.2	56	11.08	111	2.84	166	15.23	221	7.35
2	23.15	57	40.82	112	9.78	167	3.34	222	7.58
3	20.87	58	13.97	113	11.76	168	21.28	223	9.81
4	24.39	59	19.89	114	9.79	169	17.13	224	5.2
5	23.48	60	20.32	115	9.25	170	13.34	225	5.01
6	26.05	61	14.99	116	1.7	171	22.64	226	3.07
7	22.08	62	8.42	117	11.14	172	35.82	227	2.25
8	22.9	63	10.94	118	12.49	173	20.41	228	2.75
9	22.02	64	3.72	119	10.02	174	19.09	229	4.44
10	23.27	65	23.8	120	13.93	175	5.33	230	13.4
11	22.33	66	24.89	121	14.52	176	20.62	231	8.69
12	16.63	67	10.8	122	22.93	177	13.18	232	10.4
13	21.46	68	9.61	123	39.82	178	9.72	233	10.78
14	19.53	69	16.13	124	20.71	179	21.23	234	8.07
15	18.58	70	4.6	125	3.36	180	18.99	235	9.64
16	24.07	71	51.22	126	20.46	181	15.06	236	10.01
17	25.5	72	50.33	127	21.2	182	16.49	237	10.88
18	23.87	73	22.14	128	20.65	183	18.13	238	14.13
19	19.91	74	23.19	129	21.57	184	34.89	239	17.6
20	19.3	75	50.32	130	19.37	185	13.54	240	1.72
21	25.34	76	42.63	131	19.21	186	10.35	241	13.78
22	17.34	77	13.34	132	19.2	187	12.54	242	2.49
23	45.23	78	9.56	133	18.64	188	12.63	243	18.54
24	20	79	29.16	134	20.68	189	10.55	244	1.74
25	22.22	80	18.66	135	10.2	190	10.88	245	14.58
26	26.72	81	3.08	136	12.73	191	9.05	246	17.04
27	12.73	82	38.91	137	15.8	192	10.5	247	3.41
28	16.53	83	19.8	138	11.71	193	7.04	248	3.41
29	12.24	84	14.99	139	17.33	194	17.23	249	21.57
30	3.17	85	16.45	140	12.12	195	14.25	250	20.61
31	6.49	86	6.14	141	12.66	196	11.05	251	11.91
32	21.15	87	1.85	142	5.69	197	11.61	252	20.09
33	41.89	88	15.93	143	1.94	198	6.02	253	20.07
34	16.42	89	13.62	144	12.23	199	5.04	254	15.45
35	22.66	90	14.69	145	19.7	200	7.56	255	21.08
36	16.31	91	10.14	146	18.49	201	4.29	256	18.14
37	24.82	92	13.19	147	17.51	202	17.2	257	11.22
38	24.03	93	11.19	148	19.89	203	4.85	258	17.92
39	13.11	94	7.22	149	18.35	204	2.32	259	4.14
40	7.56	95	5.52	150	22.75	205	3.48	260	7.76
41	44.09	96	6.95	151	17.47	206	14.42	261	6.55
42	23.36	97	5.53	152	10.98	207	6.49	262	7.5
43	9.82	98	8.27	153	18.91	208	4.43	263	8.49
44	3.83	99	8.96	154	5.72	209	7.1	264	8.72
45	18.14	100	9.55	155	15.12	210	4	265	7.98
46	14.96	101	12.9	156	1.71	211	1.73	266	8.4
47	2.88	102	14.41	157	3.93	212	18.9	267	18.3
48	16.61	103	16.73	158	8.28	213	3.47	268	15.7
49	19.18	104	22.5	159	10.54	214	10.2	269	7.33
50	13.79	105	10.02	160	10.54	215	8.95	270	15.3
51	16.74	106	10.63	161	22.35	216	11.02	271	13.92
52	8.43	107	9.27	162	20.42	217	13.61	272	7.62
53	14.39	108	11.48	163	19.16	218	11.66	273	21.81
54	48.51	109	10.4	164	3.46	219	9.26	274	1.78
55	6.96	110	8.86	165	17.86	220	7.77	275	18.17

Table A.3 (cont'd)

Node no	Pressure (m)	Node no	Pressure (m)	Node no	Pressure (m)	Node no	Pressure (m)	Node no	Pressure (m)
276	12.83	331	19.48	386	27.09	441	15.81	496	5.33
277	10.76	332	20.09	387	16.17	442	18.9	497	6.09
278	10.97	333	19.37	388	13.06	443	12.21	498	4.8
279	11.53	334	18.87	389	1.74	444	17.24	499	5.45
280	12.22	335	19.09	390	14.18	445	16.98	500	5.51
281	4.88	336	17.87	391	11.38	446	16.38	501	16.09
282	13.97	337	17.74	392	11.09	447	16.64	502	15.56
283	4.54	338	18.81	393	12.13	448	16.04	503	8.18
284	2.15	339	18.75	394	15.23	449	16.41	504	8.44
285	5.86	340	12.45	395	15.07	450	16.67	505	17.33
286	4.7	341	22.97	396	14.86	451	16.97	506	9.07
287	4.84	342	17.4	397	13.45	452	12.01	507	3.42
288	13.14	343	25.26	398	13.96	453	3.83	508	1.93
289	1.77	344	17.92	399	13.2	454	15.95	509	32.31
290	3.89	345	17.74	400	10.8	455	15.8	510	9.53
291	15.54	346	17.55	401	8.94	456	14.53	511	8.52
292	7.13	347	17.92	402	18.46	457	15.55	512	17.66
293	14.87	348	18.16	403	30.58	458	15.05	513	12.62
294	17.55	349	17.15	404	14.17	459	15.04	514	11.57
295	6.9	350	16.56	405	8.14	460	18.42	515	9.47
296	2.52	351	17.09	406	10.1	461	16.01	516	14.64
297	11.82	352	16.11	407	7.97	462	15.26	517	17.22
298	5.9	353	15.65	408	2.07	463	5.83	518	2.47
299	13.89	354	19.2	409	6.27	464	18.13	519	2.48
300	12.32	355	14.76	410	2.41	465	14.54	520	11.48
301	10.15	356	14.5	411	4.64	466	10.11	521	11.14
302	14.93	357	14.62	412	2.92	467	10.46	522	1.89
303	10.8	358	16.21	413	4.22	468	7.08	523	13.04
304	11.46	359	9.73	414	16.18	469	20.77	524	23.32
305	20.26	360	10.86	415	16.07	470	28.9	525	8.46
306	10.52	361	21.09	416	7.46	471	9.55	526	24.55
307	7.19	362	12.97	417	2.8	472	11.4	527	12.83
308	12.04	363	11.9	418	3.33	473	16.34	528	12.83
309	2.82	364	47.69	419	2.05	474	15.55	529	17.14
310	10.81	365	18.03	420	2.14	475	13.37	530	16
311	9.24	366	18.93	421	6.91	476	5.72	531	15.86
312	7.82	367	19.66	422	11.52	477	15.89	532	17.24
313	5.92	368	31.22	423	11.13	478	22.89	533	15.73
314	10.95	369	19.15	424	10.44	479	14.8	534	15.38
315	10.97	370	42.46	425	9.54	480	15.8	535	15.62
316	20.56	371	23.76	426	11.06	481	15.32	536	26.13
317	21.26	372	12.26	427	10.2	482	18.09	537	15.21
318	18.38	373	18.76	428	2.1	483	17.45	538	16
319	17.22	374	20.59	429	1.95	484	12.84	539	15.7
320	10.05	375	18.8	430	6.51	485	11.87	540	16.23
321	18.21	376	28.51	431	3.5	486	10.81	541	16.38
322	4.99	377	19.47	432	3.21	487	11.19	542	14.73
323	14.19	378	18.05	433	2.58	488	9.74	543	3.41
324	19.17	379	19.33	434	2.46	489	9.8	544	7.45
325	41.39	380	18.24	435	9.24	490	10.55	545	8.96
326	18.89	381	17.69	436	9.75	491	8.36	546	8.65
327	19.23	382	16.78	437	12.51	492	8.85	547	5.47
328	12.74	383	16.97	438	13.12	493	8.76	548	7.03
329	18.31	384	17.96	439	24.38	494	8.24	549	19.61
330	18.68	385	21.88	440	24.38	495	6.24	550	15.86

Table A.3 (cont'd)

Node no	Pressure (m)	Node no	Pressure (m)	Node no	Pressure (m)	Node no	Pressure (m)	Node no	Pressure (m)
551	16.85	606	12.96	661	24.41	716	36.64	771	10.86
552	16.43	607	12.67	662	10.67	717	2.39	772	9.69
553	15.16	608	9.87	663	10.35	718	2.42	773	2.49
554	7.49	609	11.98	664	14.61	719	9.86	774	7.7
555	6.61	610	12.07	665	19.22	720	14.39	775	1.84
556	8.24	611	11	666	8.12	721	15.57	776	10.99
557	5.48	612	11.48	667	8.79	722	3.64	777	9.4
558	7.32	613	3.75	668	17.6	723	2.61	778	18.87
559	6.81	614	24.26	669	14.82	724	3.33	779	27.42
560	16.04	615	11.89	670	10.6	725	5.21	780	4.83
561	15.34	616	5.61	671	10.08	726	13.81	781	3.85
562	17.39	617	6.82	672	13.76	727	2.38	782	2.42
563	16.29	618	9.68	673	16.06	728	18.68	783	33.57
564	16.07	619	4.33	674	3.22	729	12.47	784	22.29
565	15.55	620	15.75	675	2.16	730	24.09	785	22.69
566	12.69	621	10.77	676	11.69	731	4.06	786	21.67
567	13.36	622	13.98	677	12.64	732	12.84	787	20.94
568	14.84	623	11.8	678	23.09	733	10.3	788	40.78
569	14.91	624	8.06	679	6.59	734	49.25	789	41.21
570	14.8	625	6.8	680	7.46	735	25.32	790	41.23
571	14.8	626	7.36	681	2.33	736	25.54	791	34.56
572	5.18	627	9.63	682	3.73	737	17.43	792	34.82
573	20.53	628	6	683	19	738	9.48	793	6
574	21.52	629	5.27	684	6.21	739	4.78	794	4.16
575	12.1	630	12.85	685	5.52	740	11.79	795	3.91
576	11.64	631	11.45	686	3.84	741	7.64	796	3.75
577	6.46	632	18.16	687	21.86	742	12.43	797	3.7
578	11.66	633	17.16	688	20.69	743	9.44	798	3.64
579	11.03	634	7.32	689	3.26	744	4.35	799	3.55
580	10.74	635	6.11	690	18.71	745	23.06	800	3.54
581	10.88	636	4.52	691	23.3	746	12.79	801	1.85
582	10.67	637	3.94	692	16.85	747	10.89	802	20.47
583	9.91	638	5.2	693	22.09	748	6.93	803	36.69
584	9.01	639	12.92	694	6.22	749	2.92	804	1.85
585	6.27	640	5.44	695	6.15	750	5.98	805	2.44
586	7.59	641	10.47	696	15.55	751	18.05	806	3.44
587	9.12	642	2.11	697	11.35	752	18.52	807	2.62
588	5.92	643	28.9	698	16.88	753	2.43	808	4.01
589	5.13	644	16.41	699	25.44	754	15.05	809	3.75
590	9.83	645	5.24	700	18.42	755	12.63	810	4.81
591	9.25	646	19.53	701	17.36	756	4.84	811	5.07
592	15.39	647	20.28	702	2.29	757	19.95	812	4.66
593	15.01	648	17.97	703	19.12	758	10.55		
594	14.87	649	18.28	704	5.94	759	2.95		
595	15.09	650	16.65	705	3.5	760	3.43		
596	15.07	651	4.5	706	5.96	761	2.58		
597	14.7	652	5.22	707	17.7	762	6.18		
598	13.32	653	2.89	708	16.7	763	4.01		
599	13.15	654	6.21	709	6.8	764	4.24		
600	13.33	655	12.83	710	3.78	765	5.42		
601	12.21	656	13.25	711	3.02	766	3.17		
602	14.47	657	13.23	712	4.55	767	8.62		
603	14.22	658	7.56	713	3.8	768	7.51		
604	15.41	659	7.59	714	2.25	769	12.43		
605	15.02	660	20.24	715	16.89	770	12.38		